



Thanks for Stimulating Collaboration!

- ▶ Interactive learning modules
 - ▶ PID control
 - ▶ Feedforward control
 - ▶ Tuning and adaptation
 - ▶ Event based control
- Tore and I are very grateful for the excellent interactions.

Research Goals

Primary goals:

- ▶ New edition of Advanced PID Control
- ▶ Develop basis for a new generation of auto-tuners
- ▶ Understand trade-offs between performance (load disturbance attenuation, measurement noise injection) and robustness
- ▶ Understand when FOTD models are sufficient and when better modeling is required - Can design be based on FOTD models

Secondary goals:

- ▶ Understand current tuning rules: Lambda, SIMC, AMIGO
- ▶ Design rules for noise filtering
- ▶ Suitable optimization methods

Some Recent Papers

- ▶ Hast, Åström, Bernhardsson, Boyd PID Design by Convex Concave Optimization. ECC 2013
- ▶ Garpinger, Åström, Häggglund Performance and robustness trade-offs in PID Control. Journal of Process Control, 24:5(2014) 568-577.
- ▶ Romero Segovia, Häggglund Åström Measurement noise filtering for PID controllers JPC 24(2014) 299-313
- ▶ Romero Segovia, Häggglund Åström Measurement noise filtering for common PID tuning rules CEP 32(2014) 43-63
- ▶ Berner, Åström, Häggglund Towards a New Generation of Relay Autotuners IFAC World Congress 2014
- ▶ Garpinger, Häggglund Modeling for Optimal PID Design. IFAC World Congress 2014
- ▶ Boyd, Hast, Åström. MIMO PID Tuning via Iterated LMI Restriction. Submitted Automatica 2014

Outline

1. Introduction
2. Performance and Robustness
3. Performance and Measurement Noise
4. Optimization
5. Next Generation Auto-tuners
6. Summary

Design Criteria

- ▶ A trade-off between conflicting requirements
 - Load disturbance attenuation
 - Robustness to process uncertainty
 - Measurement noise
 - Setpoint response
- ▶ Set-point response can be treated separately (2 DOF setpoint weighting)

Performance:

$$IE = \int_0^{\infty} e(t)dt = 1/k_i, \quad IAE = \int_0^{\infty} |e(t)|dt$$

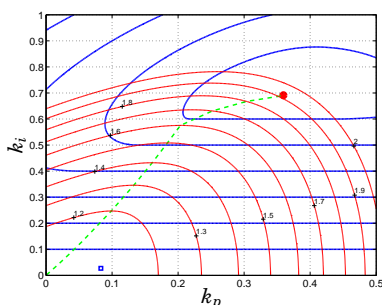
Robustness:

$$M_s = \max_{\omega} \left| \frac{1}{1 + P(i\omega)C(i\omega)} \right|, \quad M_t = \max_{\omega} \left| \frac{P(i\omega)C(i\omega)}{1 + P(i\omega)C(i\omega)} \right|$$

Measurement noise: Noise gain, SDU, filtering

Level Curves for Performance and Robustness

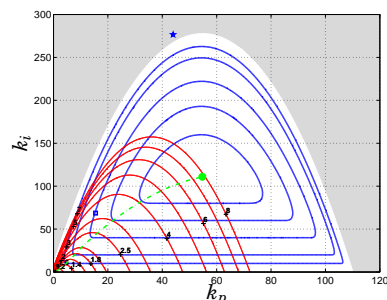
- ▶ Performance (IAE= $1/k_i$ blue) and robustness (M_s, M_t red)
- ▶ IE level curves are horizontal lines



Approximately: k_i gives performance and k_p sets robustness

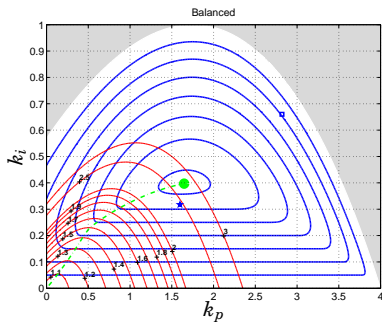
PI Control – Lag-Dominated Dynamics

- ▶ $P(s) = 1/((s+1)(0.1s+1)(0.01s+1)(0.001s+1))$, $\tau = 0.067$
- ▶ Unconstrained optimal controller poor robustness $M_s = 8!$
- ▶ ZN step \square and ZN frequency \star



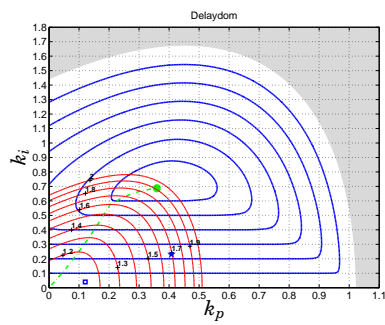
PI Control – Balanced Dynamics

- ▶ $P(s) = 1/(s + 1)^4, \tau = 0.33$
- ▶ Unconstrained optimal controller has robustness $M_s = 2.8$
- ▶ ZN step \square and ZN frequency \star

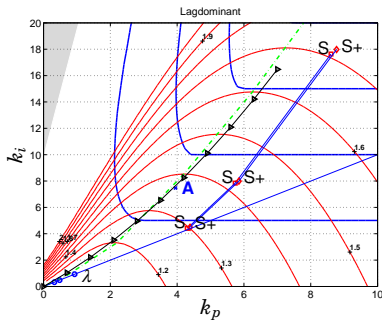


PI Control – Delay-Dominated Dynamics

- ▶ $P_1(s) = e^{-s}/(1 + 0.05s)^2, \tau = 0.92$
- ▶ Unconstrained optimal controller has robustness $M_s = 2!$
- ▶ IE and IAE minimization equivalent for small M_s, M_t

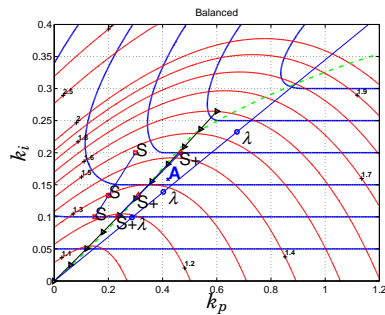


Tuning – Lag-Dominated Dynamics



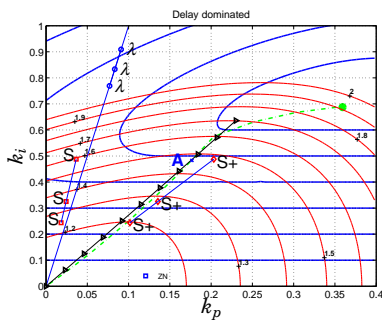
- ▶ Lambda tuning has very low gains
- ▶ S and S+ give similar tuning
- ▶ Lambda tuning gives constant integral time $T_i = k_p/k_i$

Tuning – Balanced Dynamics



- ▶ Tuning methods S+, A and λ gives similar results
- ▶ All controllers have constant integral time $T_i = k_p/k_i$

Tuning Delay-Dominated Dynamics

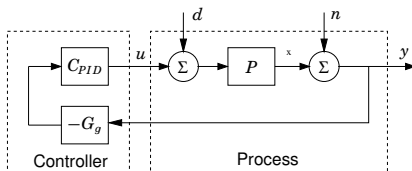


- ▶ Lambda tuning too high integral gain
- ▶ Obvious why Skogestad modified his method
- ▶ All controllers have constant integral time $T_i = k_p/k_i$

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Measurement Noise



Controller transfer function

$$G_f = \frac{1}{1 + sT_f + s^2T_f^2/2} \quad C_{PID}(s) = k_p + \frac{k_i}{s} + k_d s, \quad C = C_{PID}G_f$$

Transfer function from noise to control signal

$$-G_{un}(s) = \frac{C}{1 + PC} = SC$$

For controllers with integral action we have $G_{un}(0) = 1/K$ where $P(0) = K$.

Approximation of G_{un}

We have $S \approx \frac{s}{s + Kk_i}$ for s small, and $S \approx 1$ large s

$$-G_{un}(s) = \frac{C}{1 + PC} = SC \approx \frac{k_i + k_p s + k_d s^2}{(s + Kk_i)(1 + sT_f + (sT_f)^2/2)}$$

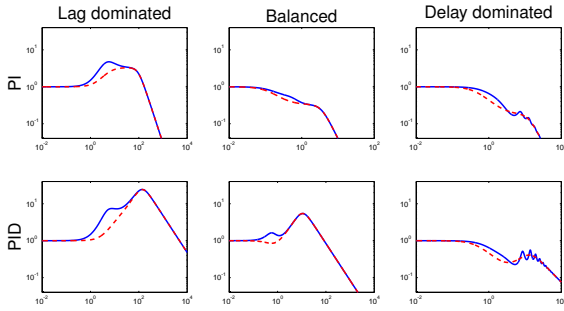
For low frequencies (small s) the numerator of G_{un} is dominated by the integral gain k_i and we have

$$C_{PID}(s) \approx \frac{k_i}{s}, \quad G_f(s) \approx 1, \quad S(s) \approx \frac{s}{s + Kk_i}$$

Hence

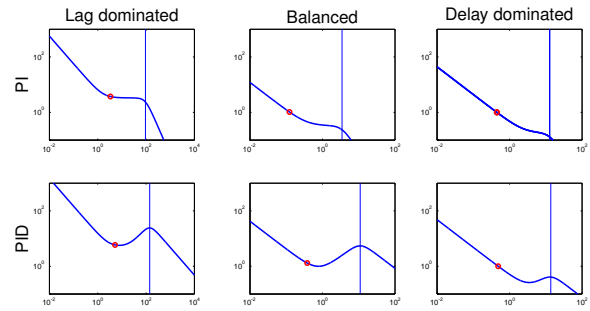
$$G_{un}(s) \approx G_{un}^{PID} = -\frac{k_i + k_p s + k_d s^2}{(s + Kk_i)(1 + sT_f + (sT_f)^2/2)}$$

Bode Plots of Noise Transfer Function G_{un}



- ▶ Validity of approximation (error in mid frequency range M_s peak)
- ▶ Differences PI/PID lag dominated/delay dominated

Bode Plots Controller Transfer Function C



- ▶ Gain crossover frequency
- ▶ Frequency $\omega_f = \sqrt{2}/T_f$

Stochastic Modeling

Measurement noise stationary with spectral density $\Phi(\omega)$

$$\sigma_u^2 = \int_{-\infty}^{\infty} |G_{un}(i\omega)|^2 \Phi(\omega) d\omega$$

$$\sigma_{y_f}^2 = \int_{-\infty}^{\infty} |G_f(i\omega)|^2 \Phi(\omega) d\omega$$

$$G_{un}(s) \approx -\frac{k_i + k_p s + k_d s^2}{(s + K k_i)(1 + s T_f + (s T_f)^2/2)}$$

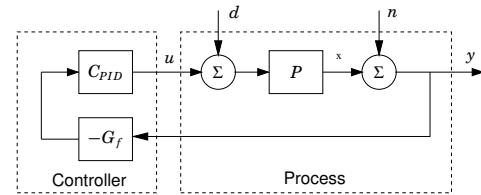
White noise

$$\sigma_u^2 \approx \pi \left(\frac{k_i}{K} + \frac{k_p^2 - 2k_i k_d}{T_f} + 2 \frac{k_d^2}{T_f^3} \right) \Phi_0, \quad \sigma_{y_f}^2 = \frac{\pi}{T_f} \Phi_0$$

Noise gain

$$k_{nw} = \frac{\sigma_u}{\sigma_{y_f}} \approx \sqrt{\frac{k_i T_f}{K} + k_p^2 - 2k_i k_d + 2 \frac{k_d^2}{T_f^2}}$$

Finding a Suitable Filter Time Constant



$$G_f = \frac{1}{1 + s T_f + s^2 T_f^2/2} \quad C_{PID}(s) = k_p + \frac{k_i}{s} + k_d s, \quad C = C_{PID} G_f$$

- ▶ Develop sound design procedure for PI and PID control of a given process
- ▶ Apply procedure to a representative test batch
- ▶ Analyse results to find insights and understanding
- ▶ Explore and try to find simple design rules

Finding a Suitable Filter Time Constant

An iterative design procedure

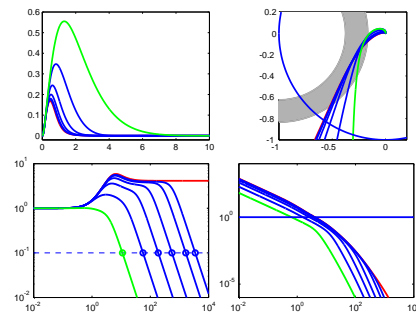
1. Design controller for nominal process P_0 e.g. by minimizing IAE subject to robustness constraints, $G_f = 1$.
2. Compute ω_{gc} for $P G_f$
3. Choose $T_f = \alpha / \omega_{gc}$, $\alpha = 0.01, 0.02, 0.05, 0.01, 0.15, 0.2$
4. Repeat from 2 with until convergence
5. Make trade-off plots (load disturbance attenuation-noise injection)

Can be applied to any design procedure, particularly simple for design methods based on the FOTD model.

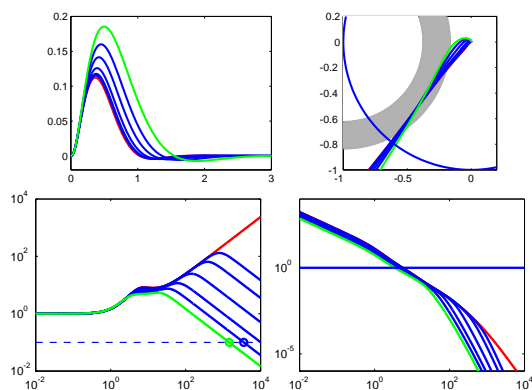
PI Control Lag-dominant Dynamics

$$P_1(s) = \frac{1}{(s+1)(0.1s+1)(0.01s+1)(0.001s+1)}$$

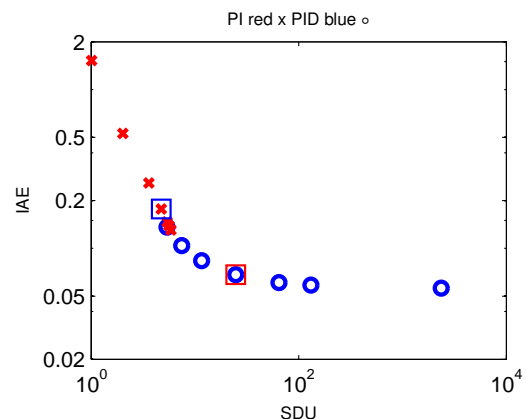
FOTD parameters: $K = 1$, $T = 1.04$, $L = 0.08$, and $\tau = 0.07$



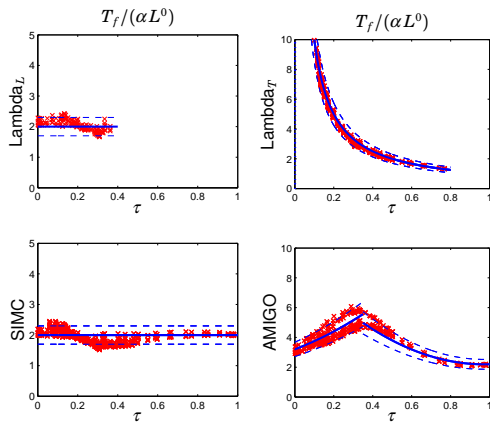
PID Control Lag-dominant Dynamics



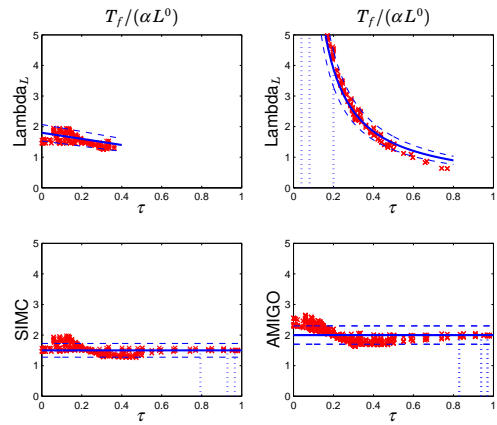
Trade-offs



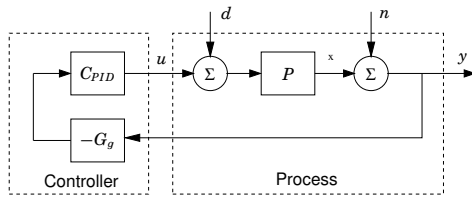
PI Control - FOTD Correlations



PID Control - FOTD Correlations



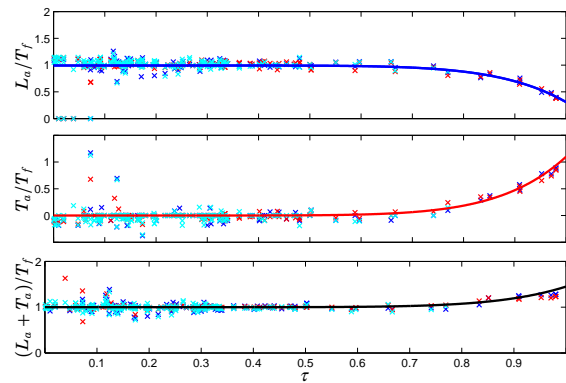
Effect of T_f on FOTD Parameters



- ▶ With filtering the effective process dynamics changes from P to PG_f
- ▶ How to determine the FOTD parameters?
- ▶ The step response method

$$L = L_0 + (1 - 0.65 \tau^8) T_f, \quad T = T_0 + 1.1 \tau^8 T_f.$$

Effect of T on FOTD Parameters



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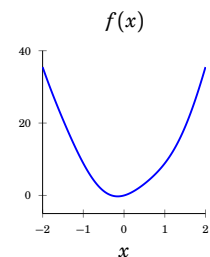
Convex Optimization

The basic convex optimization:

$$\begin{aligned} & \underset{x}{\text{minimize}} && f_0(x) \\ & \text{subject to} && f_i(x) \leq 0, \quad i = 1, \dots, m \\ & && h_j(x) = 0, \quad j = 1, \dots, n, \end{aligned}$$

$f_i(x)$, convex functions, $h_j(x)$ affine functions of x .

- ▶ If a local minimum exists it is a global minimum
- ▶ Efficient and fast numerical algorithms
- ▶ Good software tools CVX



Convex-Concave Procedure

Replace concave part by linearization around current solution point x_k

$$f(x) - g(x) \approx f(x) - g(x_k) - \nabla g(x_k)^T (x - x_k)$$

The approximated problem

$$\begin{aligned} & \underset{x}{\text{minimize}} && f_0(x) - g_0(x_k) - \nabla g_0(x_k)^T (x - x_k) \\ & \text{subject to} && f_i(x) - g_i(x_k) - \nabla g_i(x_k)^T (x - x_k) \leq 0, \quad i = 1, \dots, m \end{aligned}$$

is convex and solved to generate a new solution point x_{k+1} . Iterate until convergence.

- ▶ Composition always possible if Hessian of $f(x) - g(x)$ is bounded
- ▶ Converges to a local minimum or saddle-point.
- ▶ Sacrifices global optimality but gains convexity and hence speed.
- ▶ Feasible starting point is needed.

Convex-Concave Optimization for PID Control

Loop transfer function

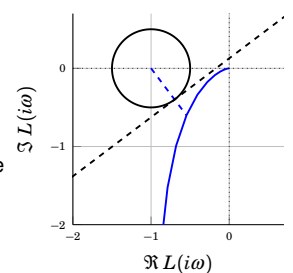
$$G_l = PG_f(k_p + \frac{k_i}{s} + k_d s)$$

is linear in the parameters k_p, k_i, k_d .

The robustness constraint that $G_l(i\omega)$ is outside the circle

$$r - |G_l - c| \leq 0$$

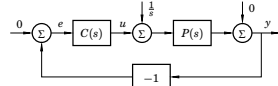
does not give a convex problem. Convex-concave optimization can be applied since G_l is linear in the parameters. For each frequency the constraint to be outside the circle is replaced by being outside a half plane (the dashed line)



Heat Rod

$$P(s) = e^{-\sqrt{s}}$$

$$C(s) = k_p + \frac{k_i}{s} + k_d s$$



Optimization problem

$$\begin{aligned} &\text{maximize } k_i \\ &\text{subject to } |S(i\omega)| \leq 1.4 \\ &\quad |T(i\omega)| \leq 1.4 \end{aligned}$$

Convex approximation

$$\begin{aligned} &\text{max. } k_i \\ &\text{s.t. } 1/1.4 - \Re\left(\frac{(L_k + 1)^+}{|L_k + 1|} (L + 1)\right) \leq 0 \\ &\quad r_T - \Re\left(\frac{(L_k - c_T)^+}{|L_k - c_T|} (L - c_T)\right) \leq 0 \end{aligned}$$

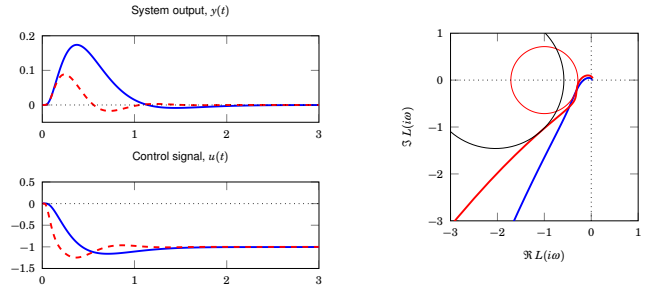
Nyquist Plot and Load Step Response

$$C_{PI}(s) = 2.94 + \frac{11.54}{s}$$

$$IE = 0.086, IAE = 0.10$$

$$C_{PID}(s) = 7.40 + \frac{48.25}{s} + 0.46s$$

$$IE = 0.021, IAE = 0.031$$

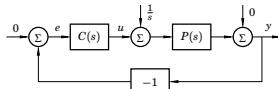


IE or IAE

Intuitively it may seem like optimization of IE or IAE will give the same result provided the system is well damped,

$$P(s) = \frac{1}{(s+1)^3}$$

$$C(s) = k_p + \frac{k_i}{s} + k_d s$$



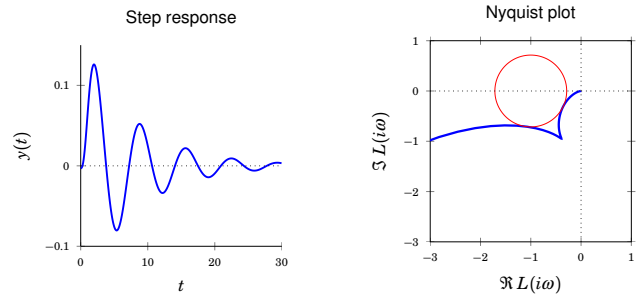
Optimization problem

$$\begin{aligned} &\text{maximize } k_i \\ &\text{subject to } |S(i\omega)| \leq 1.4 \end{aligned}$$

Convex approximation

$$\begin{aligned} &\text{max. } k_i \\ &\text{s.t. } 1/1.4 - \Re\left(\frac{(L_k + 1)^+}{|L_k + 1|} (L + 1)\right) \leq 0 \end{aligned}$$

Nyquist Plot and Step Responses



The oscillatory behavior related to cusp in Nyquist curve

Adding a Curvature Constraint

$$P(s) = \frac{1}{(s+1)^3}$$

$$C(s) = k_p + \frac{k_i}{s} + k_d s$$

Convex approximation

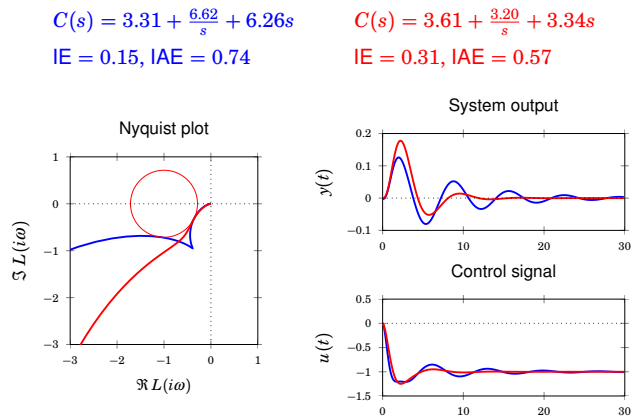
$$\begin{aligned} &\text{max. } k_i \\ &\text{s.t. } 1/1.4 - \Re\left(\frac{(L_k + 1)^+}{|L_k + 1|} (L + 1)\right) \leq 0 \\ &\quad x^T Q x + A_k x + b_k \leq 0 \end{aligned}$$

Optimization problem

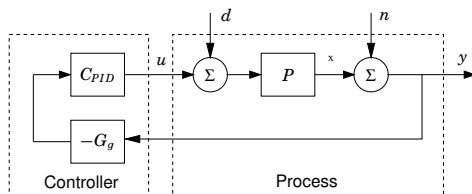
$$\begin{aligned} &\text{maximize } k_i \\ &\text{subject to } |S(i\omega)| \leq 1.4 \\ &\quad \kappa \leq 1/1.4 \end{aligned}$$

- ▶ A grid of 1000 frequencies between 10^{-2} and 10^2 rad/s.
- ▶ Solved using CVX in MATLAB.
- ▶ Converges within twelve iterations (4 s).

Nyquist Plot and Load Step Responses



Multivariable PID Controllers



Controller transfer function

$$G_f = \frac{1}{1 + sT_f + s^2T_f^2/2} \quad C_{PID}(s) = K_p + K_i \frac{1}{s} + K_d s, \quad C = C_{PID} G_f$$

Optimization: Minimize $\|(P(0)K_I)^{-1}\|$ subject to

$$\|S\|_\infty \leq S_{\max}, \quad \|T\|_\infty \leq T_{\max}, \quad \|Q = CS\|_\infty \leq Q_{\max}$$

The Wood-Berry Distillation Column

Process model

$$P(s) = \begin{bmatrix} \frac{12.8e^{-s}}{16.7s + 1} & \frac{-18.9e^{-3s}}{21.0s + 1} \\ \frac{6.6e^{-7s}}{10.9s + 1} & \frac{-19.4e^{-3s}}{14.2 + 1} \end{bmatrix}$$

Optimization

$$S_{\max} = 1.4, \quad T_{\max} = 1.4, \quad Q_{\max} = 3/\sigma_{\min}(P(0)) = 0.738.$$

- ▶ Derivative action time constant: $\tau = 0.3$
- ▶ Sampled with $N = 300$ logarithmically spaced frequency samples in the interval $[10^{-3}, 10^3]$
- ▶ Initialization: $K_P = 0, \quad K_I = \epsilon P(0)^{\dagger}, \quad K_D = 0, \quad \epsilon = 0.01.$

Wood and his Column



General and Diagonal PID Controllers

Optimal PID controller (converged in 7 iterations)
 $\|(P(0)K_I)^{-1}\| = 2.25$.

$$K_P = \begin{bmatrix} 0.1750 & -0.0470 \\ -0.0751 & -0.0709 \end{bmatrix}, \quad K_I = \begin{bmatrix} 0.0913 & -0.0345 \\ 0.0402 & -0.0328 \end{bmatrix},$$

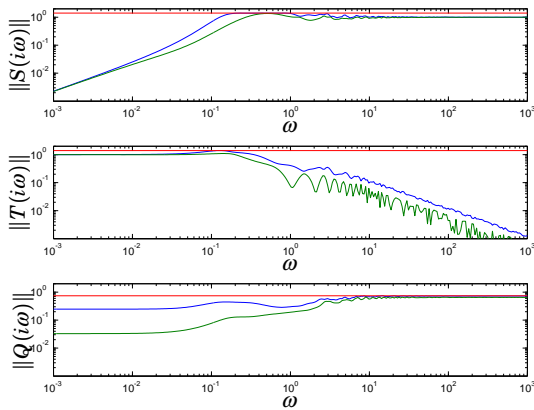
$$K_D = \begin{bmatrix} 0.1601 & -0.0051 \\ 0.0201 & -0.1768 \end{bmatrix},$$

Diagonal PID controller (converged in 8 iterations)
 $\|(P(0)K_I)^{-1}\| = 13.36$,

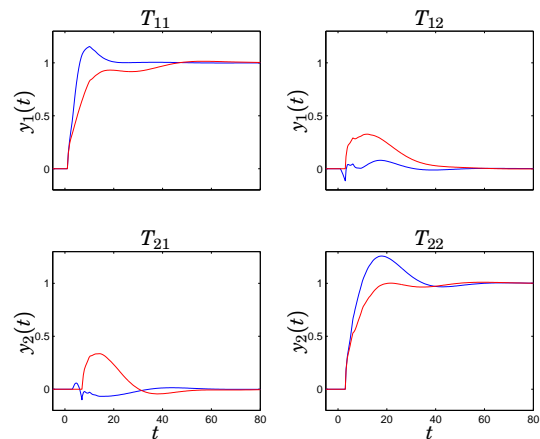
$$K_P = \begin{bmatrix} 0.1535 & 0 \\ 0 & -0.0692 \end{bmatrix}, \quad K_I = \begin{bmatrix} 0.0210 & 0 \\ 0 & -0.0136 \end{bmatrix},$$

$$K_D = \begin{bmatrix} 0.1714 & 0 \\ 0 & -0.1725 \end{bmatrix},$$

General PID Controller



Step Responses



Extensions

- ▶ Exchanging objectives and constraints
- ▶ Frequency dependent bounds
- ▶ Other closed loop transfer functions
- ▶ Low frequency disturbance attenuations
 $S(s)P(s) \approx s(P(0)K_I)^{-1}P(0)$
- ▶ High frequency roll-off
- ▶ Unstable plants
- ▶ Robustness to plant variations
- ▶ More general controllers

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Reflections

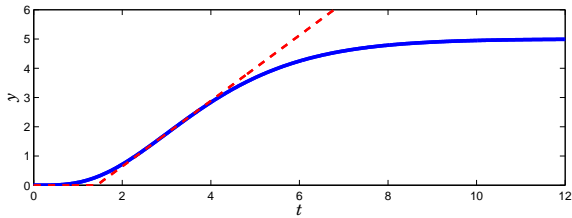
Putting it all together

- ▶ Relay feedback
- ▶ Good excitation - the secret to good modeling
 - ▶ The classic, integrators, filters, asymmetry, adaptive hysteresis
- ▶ Short experimentation time
 - ▶ Avoid waiting for steady state!
 - ▶ How short can it be?
- ▶ Design of identification experiment
 - ▶ Input signal and excitation essential!!
 - ▶ The beauty of the relay-autotuner
 - ▶ How to design the second phase? Chirp + pulse??
- ▶ How to assess a model?
 - ▶ Behavior in closed loop the primary goal!
 - ▶ Fitting error, cross-validation, AIC, Vinnicombe
- ▶ Computational issues?
 - ▶ Matlab, Python, FMI
- ▶ Implementation: Coding, box, DCS, web, cloud

Key Issues

- ▶ A long term plan - include what we have learned
- ▶ Auto-tuners for building simulation
- ▶ Auto-tuners for controllers
 - ▶ Boxes, PLCs, DCS systems
 - ▶ Simple version: PI control
 - ▶ Complex version: Selection of PI or PID and better modeling
- ▶ Criteria
 - ▶ Short experiments
 - ▶ Good robust tuning rules with design parameter
- ▶ Implementation issues
 - ▶ Stand alone box: Matlab, Python, FMI
 - ▶ SoftwareWeb, cloud

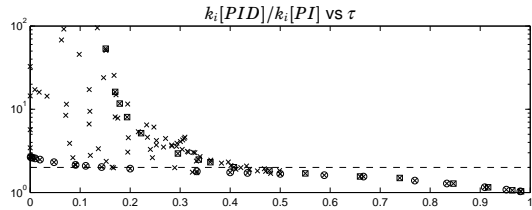
Modeling Issues



- ▶ True time delay is a fundamental limitation
- ▶ FOTD lumps true time delay and high order dynamics
- ▶ Does not matter for $\tau > 0.4$
- ▶ Better models than FOTD are required for PID control and $\tau < 0.4$

Modeling for PI & PID Control

AMIGO Tuning - complete testbatch



circles: $P(s) = \frac{K}{1+sT}e^{-sL}$, squares: $P(s) = \frac{K}{(1+sT)^2}e^{-sL}$

- ▶ FOTD OK for $\tau > 0.4$ better model required for smaller τ !
- ▶ Derivative action small improvement for $\tau > 0.8$

Models

Two parameter models

$$P(s) = \frac{b}{s+a}, \quad P(s) = K e^{-sL}$$

Three parameter models

$$P(s) = \frac{b}{s^2 + a_1s + a_2}, \quad P(s) = \frac{b}{s+a} e^{-sL}, \quad P(s) = \frac{K}{1+sT} e^{-sL}$$

$$P(s) = \frac{K}{(1+sT)^2} e^{-sL}$$

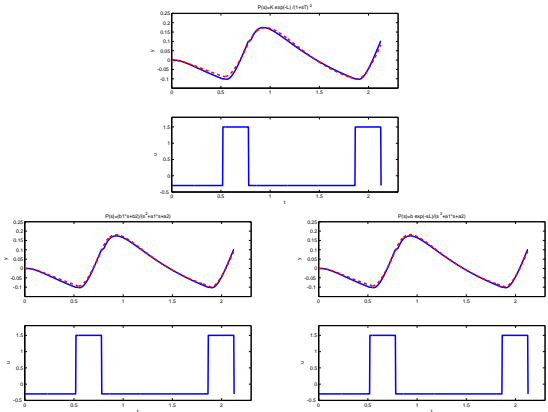
Four parameter models

$$P(s) = \frac{b_1s + b_2}{s^2 + a_1s + a_2}, \quad P(s) = \frac{b}{s^2 + a_1s + a_2} e^{-sL}$$

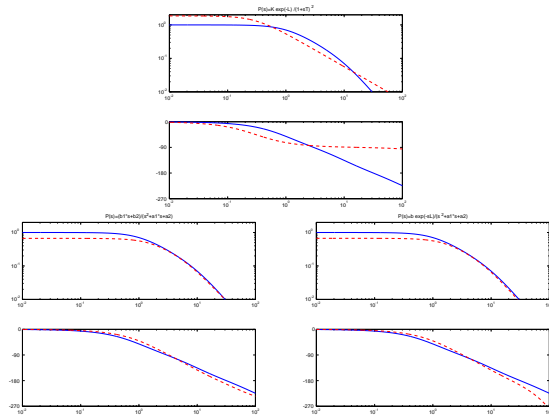
Five parameter model

$$P(s) = \frac{b_1s + b_2}{s^2 + a_1s + a_2} e^{-sL}$$

Three and Four Parameter Models



Three and Four Parameter Models



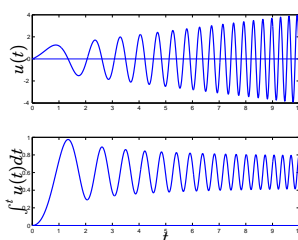
Excitation

- ▶ The key to successful system identification
- ▶ Symmetric relay dominant at one frequency
- ▶ The asymmetric relay has the dominant frequency at the period T_p , a low frequency component and some high frequencies
- ▶ Highly desirable to have excitation at other frequencies
- ▶ Modifications of the relay
 - ▶ Integrator
 - ▶ Filters
 - ▶ Change hysteresis: Ulf Holmberg
 - ▶ Mix of integrator and relay: Waller
 - ▶ Flat spectrum: Kristian
 - ▶ Asymmetric relay
- ▶ Chirp signals

The Chirp Signal

$$u(t) = (a + bt) \sin(c + dt)t$$

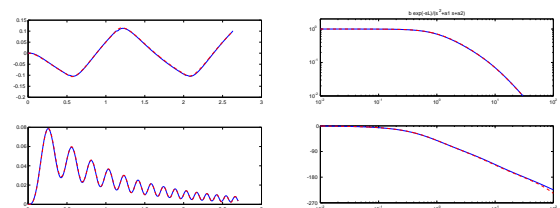
Frequency varies between a and $c + dt_{max}$ amplitude between $a + bt_{max}$



Notice both high and low frequency excitation

Asymmetric Relay and Chirp

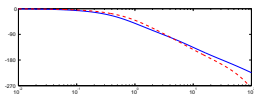
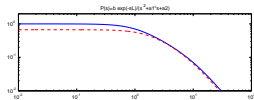
- ▶ Asymmetrical relay experiment combined chirp signal experiment
- ▶ Double experiment time. Constant amplitude, $L = 0.01, w = 15 * (1 + 0.5 * t), t_{max} = 2.7, 0.15 \leq \omega L \leq 0.35$



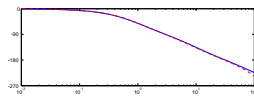
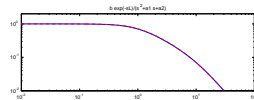
Parameters: $a_1 = 10.366 \pm 0.033$, $a_2 = 9.574 \pm 0.028$,
 $b = 9.566 \pm 0.027$, $L = 0.0109 \pm 0.0002$

Effect of Proper Excitation

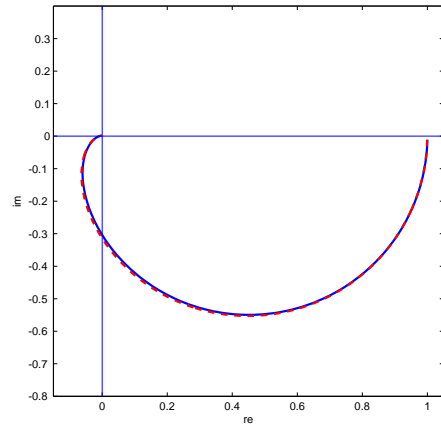
Only relay



Relay and chirp



Nyquist Plots



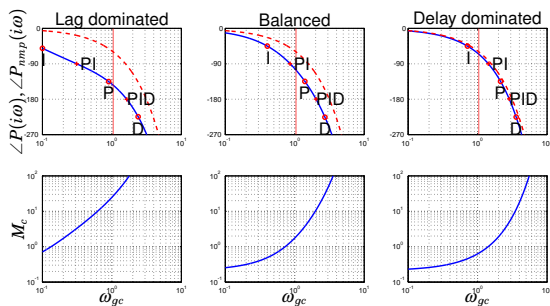
Outline

1. Introduction
2. Performance and Robustness
3. Performance and Measurement Noise
4. Optimization
5. Next Generation Auto-tuners
6. Summary

Summary

- ▶ Trade-off plots give a lot of insight
 - ▶ Effect of parameters k_i, k_p, τ
 - ▶ Assessment of tuning rules (close to green line)
- ▶ Rational ways of designing filters
 - ▶ Simple rules related to FOTD or T_i, T_d
 - ▶ The equation for noise gain
- ▶ Feedforward (not covered in the talk)
- ▶ Computations
 - ▶ PID Design Tool
 - ▶ Interactive Learning Modules
 - ▶ Convex optimization
- ▶ Automatic tuning
 - ▶ Better excitation: asymmetric relay and chirp
- ▶ How to package the results
 - ▶ Simple tuners
 - ▶ Elaborate tuners with extensive computations - cloud?
- ▶ Assessment plots

Assessment Plots



$$\omega_{gc} \approx P(0)k_i, \quad M_c = \frac{1}{|P(i\omega_{gc})|} e^{\gamma(-\arg P(i\omega_{gc}) - \pi + \phi_m)}, \quad \gamma \approx 1$$

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