Recent Advances in Paper Machine Control

Q. Lu[1], M.G. Forbes[2], R.B. Gopaluni[1], P.D. Loewen[1], J.U. Backström[2], **G.A. Dumont**[1]

1 - University of British Columbia 2 - Honeywell Process Solutions
Vancouver, Canada

LCCC Process Control Workshop – Lund - September 30, 2016

Research Interests

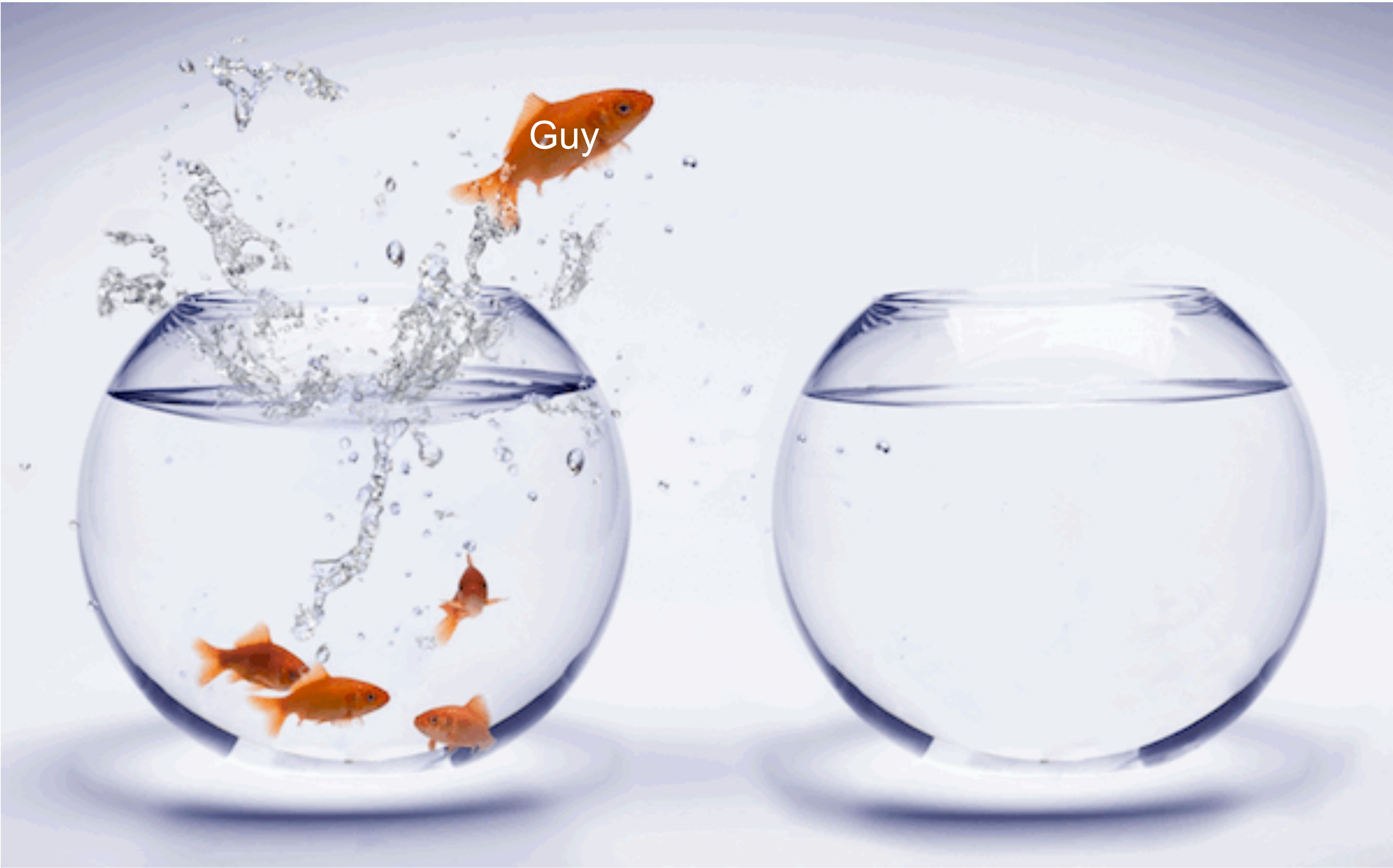
- Adaptive Control, predictive control, system identification, control of distributed parameter systems, control performance monitoring,

- Applications of advanced control to process industries, particularly **pulp and paper**:

  - Kamyr digester
  - Bleach plant
  - Thermomechanical pulping
  - **Paper machine**.

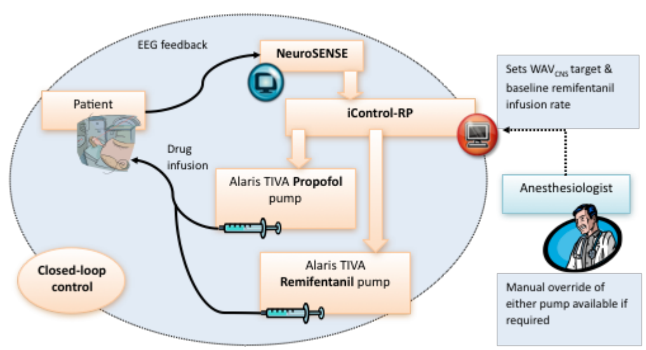
My Research Lab then….

Honeywell

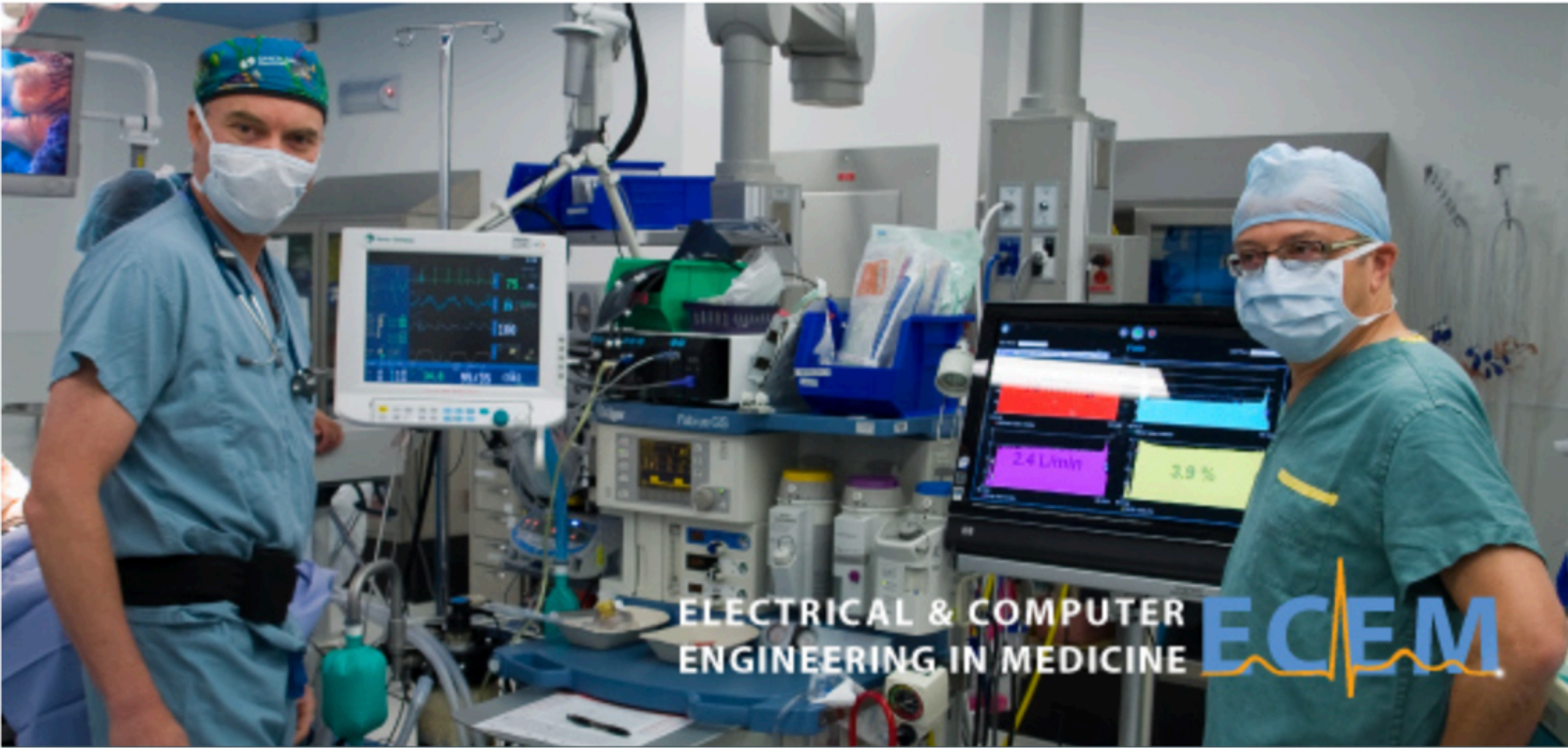

Guy

Research Interests

- Biomedical applications of control and signal processing:
  - Automatic drug delivery, closed-loop control of **anesthesia**,
  - Physiological monitoring in the OR and ICU, modeling and
  - Identification of physiological systems (cardiovascular system, circadian rhythms),
  - Biosignal processing (EEG, ECG, etc...), detection of epileptic seizures,
  - Identification of the dynamics of the autonomic nervous system,
  - Low-cost mobile health technology for **global health**

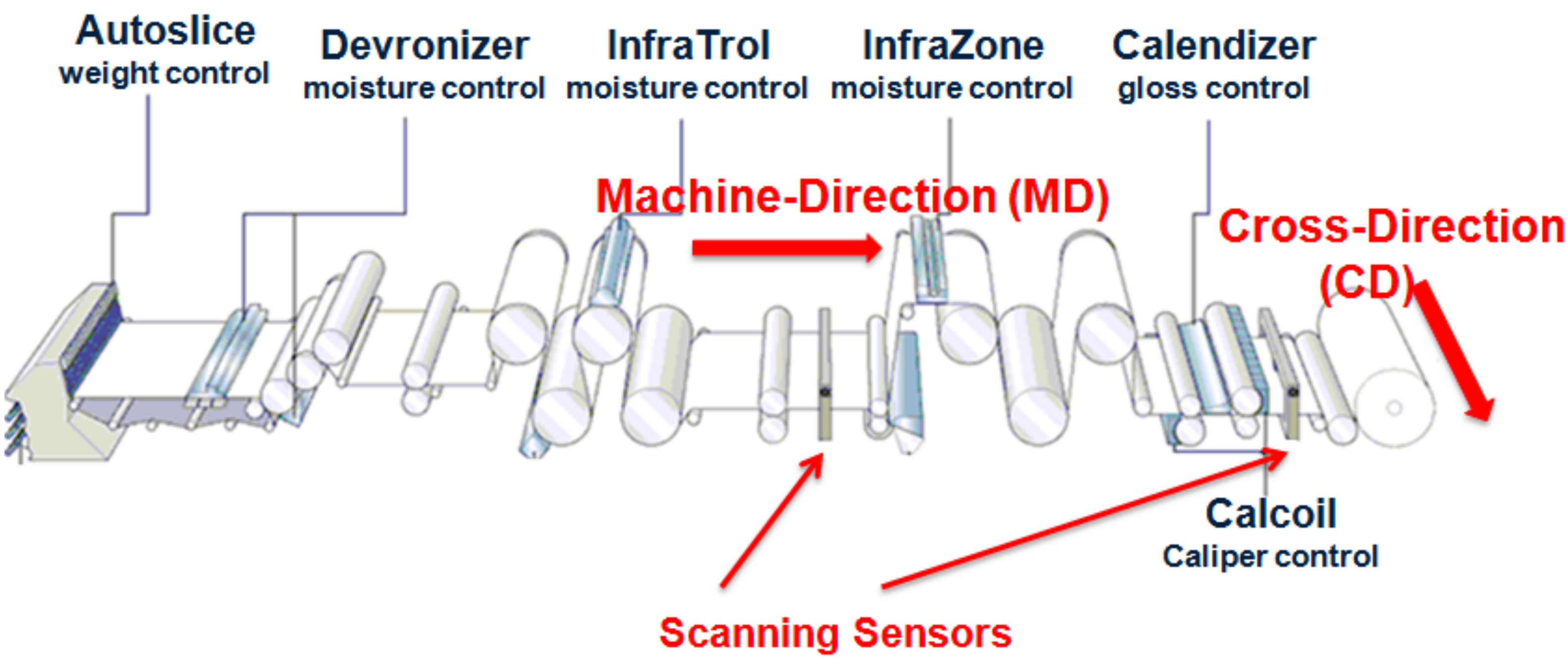


My Research Lab now…



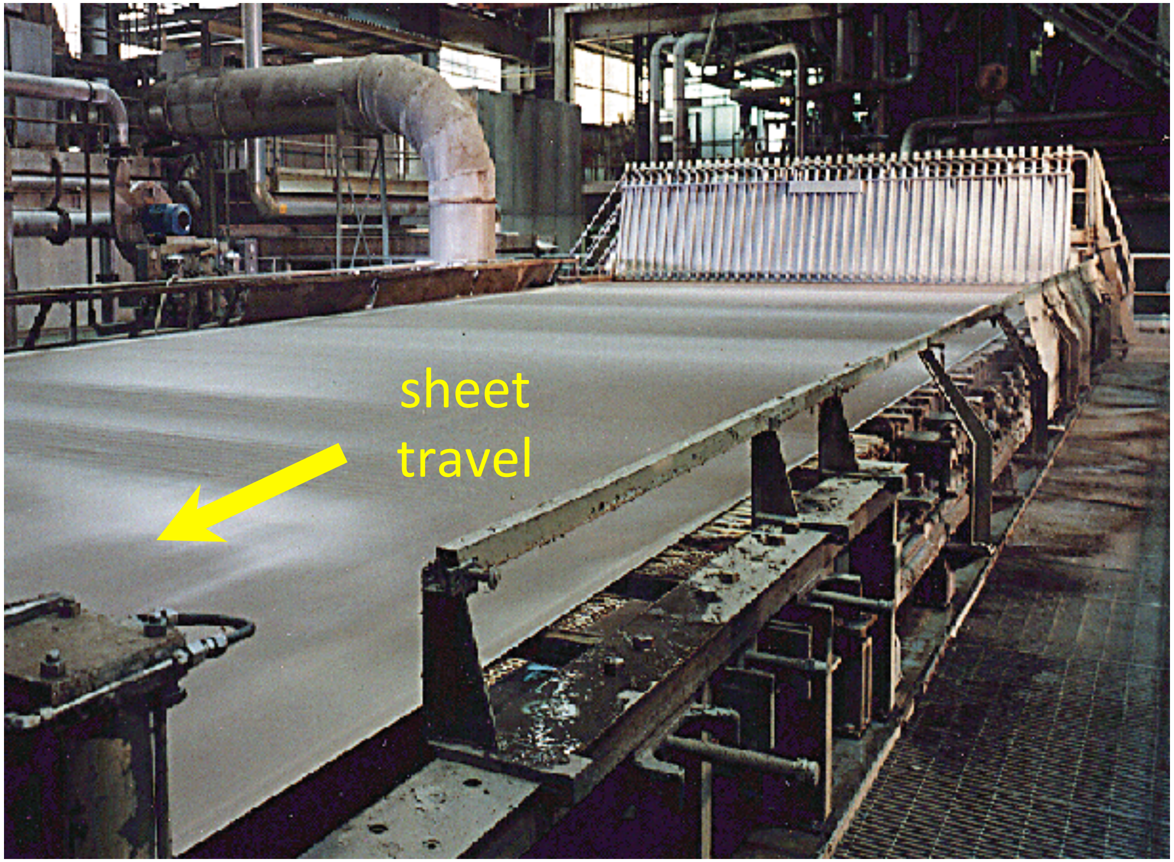
Back to the Paper Machine

- We have been collaborating with Honeywell Process Solutions since 1986



Honeywell

- Pulp stock is extruded on to a wire screen up to 11m wide and may travel faster than 100km/h.

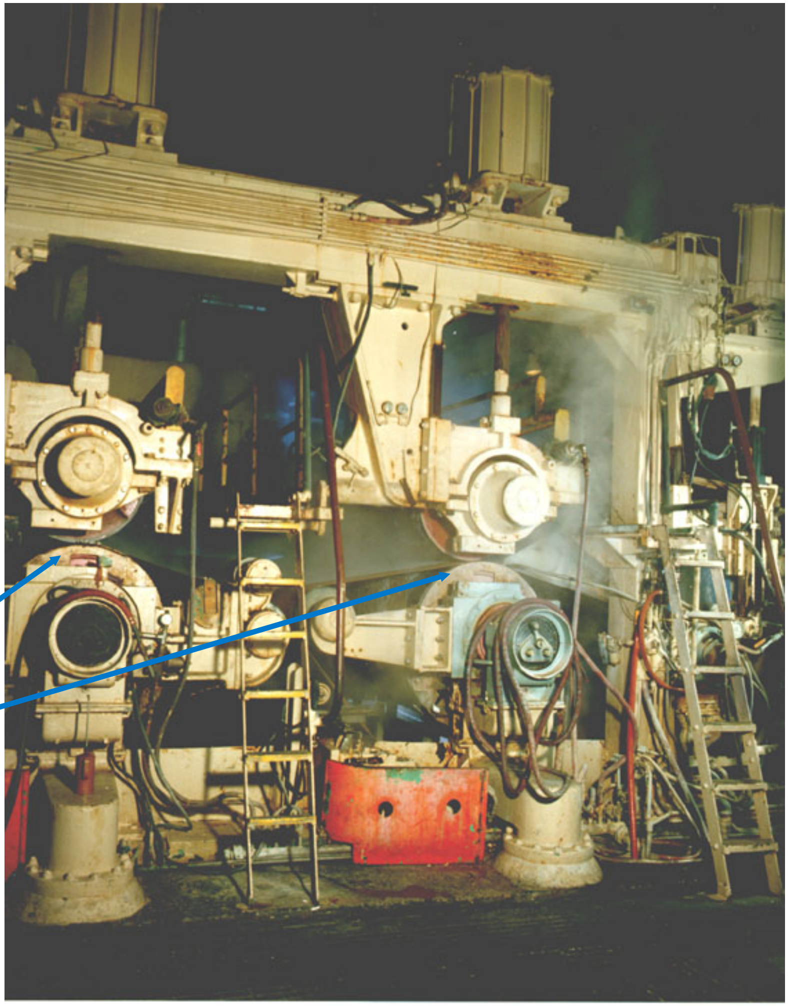


Initially, the pulp stock is composed of about 99.5% water and 0.5% fibres.

Honeywell

- Newly-formed paper sheet is pressed and further de-watered.

suction presses



- The pressed sheet
  is then dried to moisture
  specifications

finished reel

The paper machine pictured
is 200 metres long and the paper sheet
travels over 400 metres.

Honeywell

scanner

- The finished paper sheet is wound up on the reel.

The moisture content at the dry end is about 5%. It began as pulp stock composed of about 99.5% water.

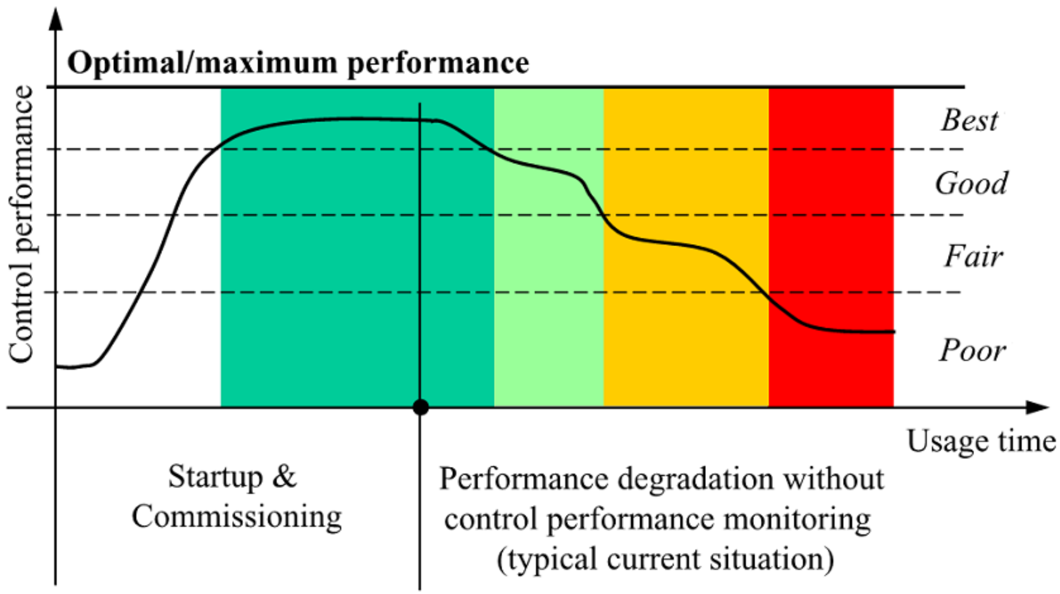
Honeywell

Outline

- Introduction
- Adaptive control for the MD process
- Adaptive control for the CD process
- Summary

Motivations

- For most paper machines, the initial controller is used for months even years without retuning the controller.
- Dynamics of paper machines vary over time due to changes in operation conditions.
- Control performance may deteriorate due to some factors, e.g., irregular disturbance, model-plant mismatch.



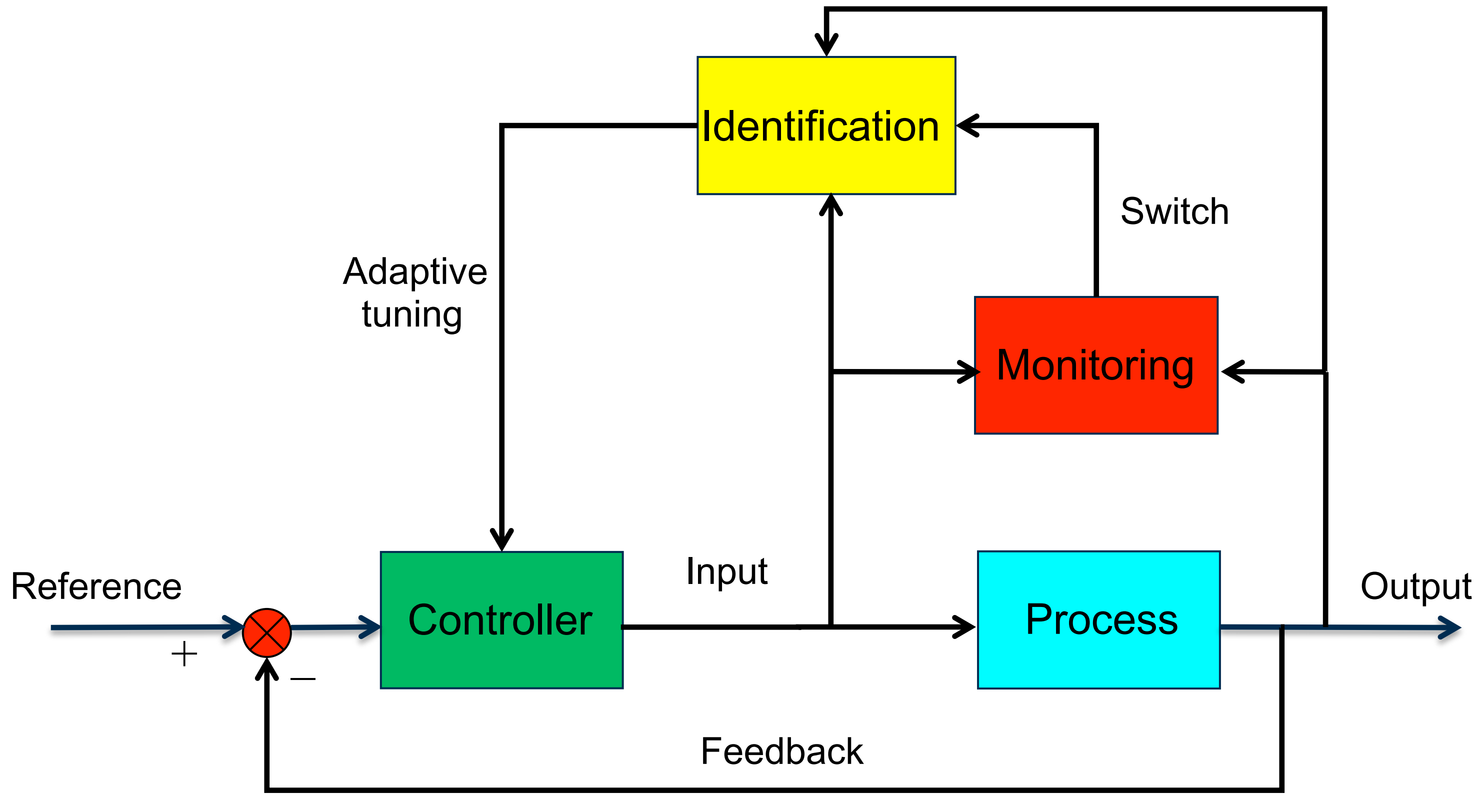
Control performance vs. usage time (M. Jeliali, Springer, 2013)

Objectives

- Monitoring controller performance online for MD and CD processes.
- Identifying whether model-plant mismatch happens.
- Re-identifying process model in the case of significant mismatch:
  - Optimal input design in closed-loop;
  - Closed-loop identification.
- Re-tuning controllers based on updated process model.
- Performing this adaptive scheme in closed-loop without interrupting the process or user intervention.

Adaptive Control Framework

- Adaptive control scheme for both MD and CD



- Monitoring includes control performance assessment and model-plant mismatch detection.

Adaptive Control for the Machine-Directional Process of Paper Machines

Outline

- Performance monitoring
- Model-plant mismatch detection
- Optimal input design
- Summary

Honeywell

Performance Monitoring

- Minimum variance benchmark: time-delay as the main performance limitation.
- Decompose output into controller-invariant and controller-dependent

$$y(t) = \underbrace{f_0 e(t) + f_1 e(t-1) + \cdots + f_{d-1} e(t-d+1)}_{F(q^{-1})\ \text{controller-invariant}} + R(z^{-1}) e(t-d)$$

- MVC performance index

$$\eta = \frac{var[Fe(t)]}{var[y(t)]}$$

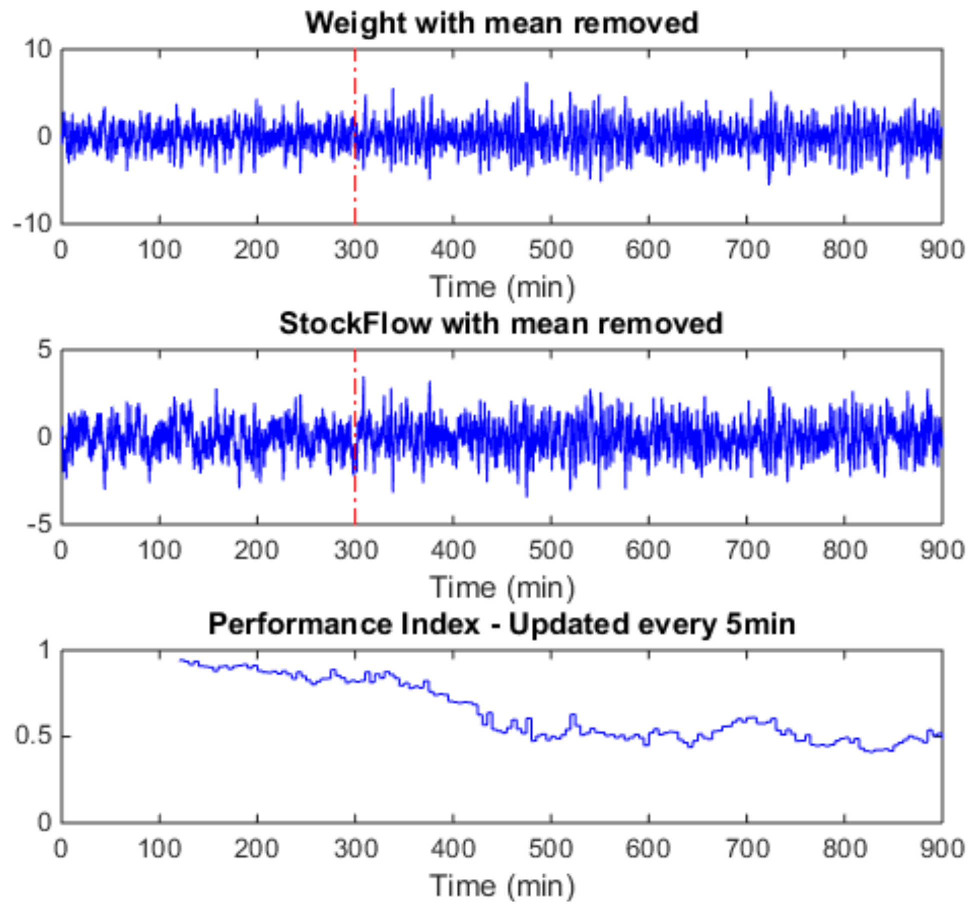
- Moving average modeling of $y(t)$ to estimate performance index.

Performance Monitoring Example

- Introduce a gain mismatch at time t=300 min

Pitfalls of using MVC or MVC-like benchmark to detect mismatch:

- Various factors can degrade performance index;
- Not able to discriminate mismatch from other causes;
- Noise model change can degrade PI but should not trigger an identification.



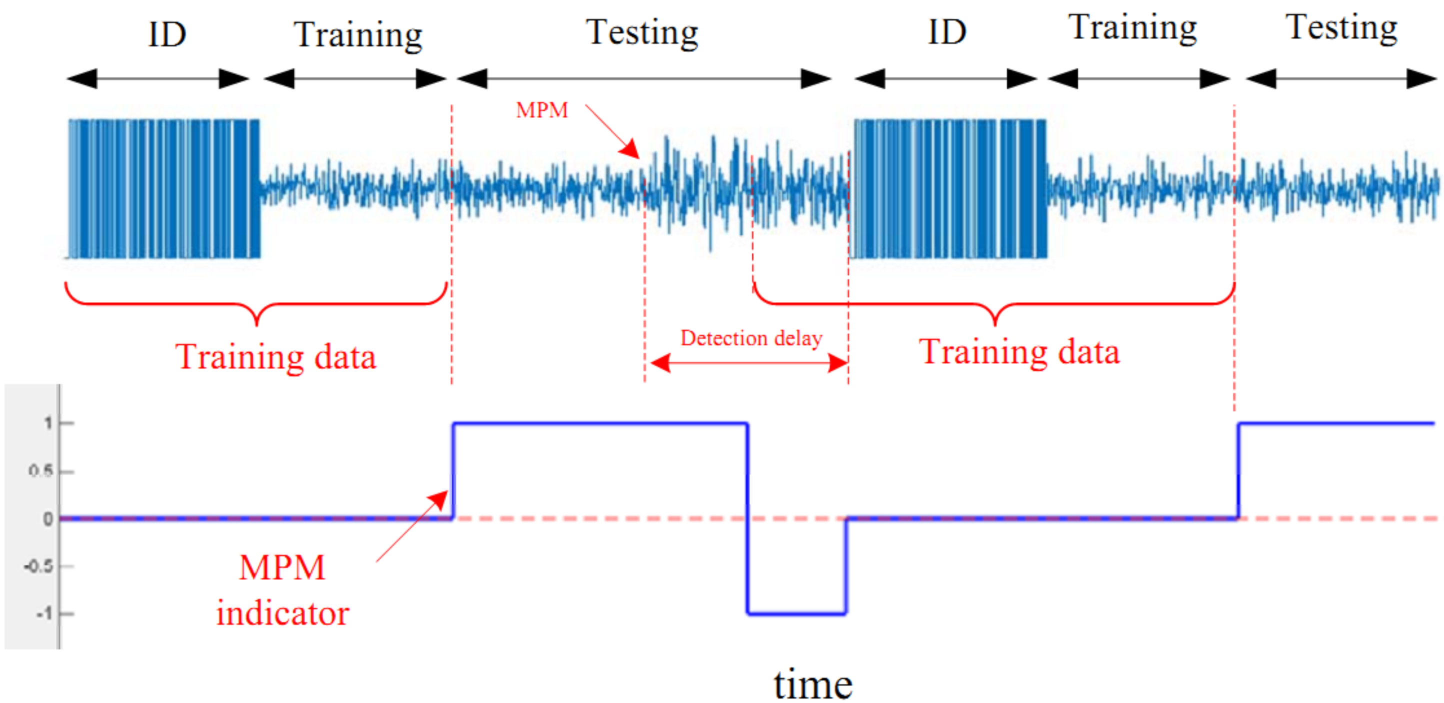
Honeywell

Model-Plant Mismatch Detection

- Mismatch detection is the core of our adaptive control scheme.
- Objective: a method to directly detect mismatch online, with routine operating data that may lack any external excitations.
- Difficulty: large variance on parameter estimates; limited amount of data.
- Idea: using a period of 'good data' as benchmark and compare it with the data under test.
- Techniques: a novel consistent closed-loop identification method; train support vector machine (SVM) with 'good data'; predict mismatch with SVM on testing data.

Model-Plant Mismatch Detection

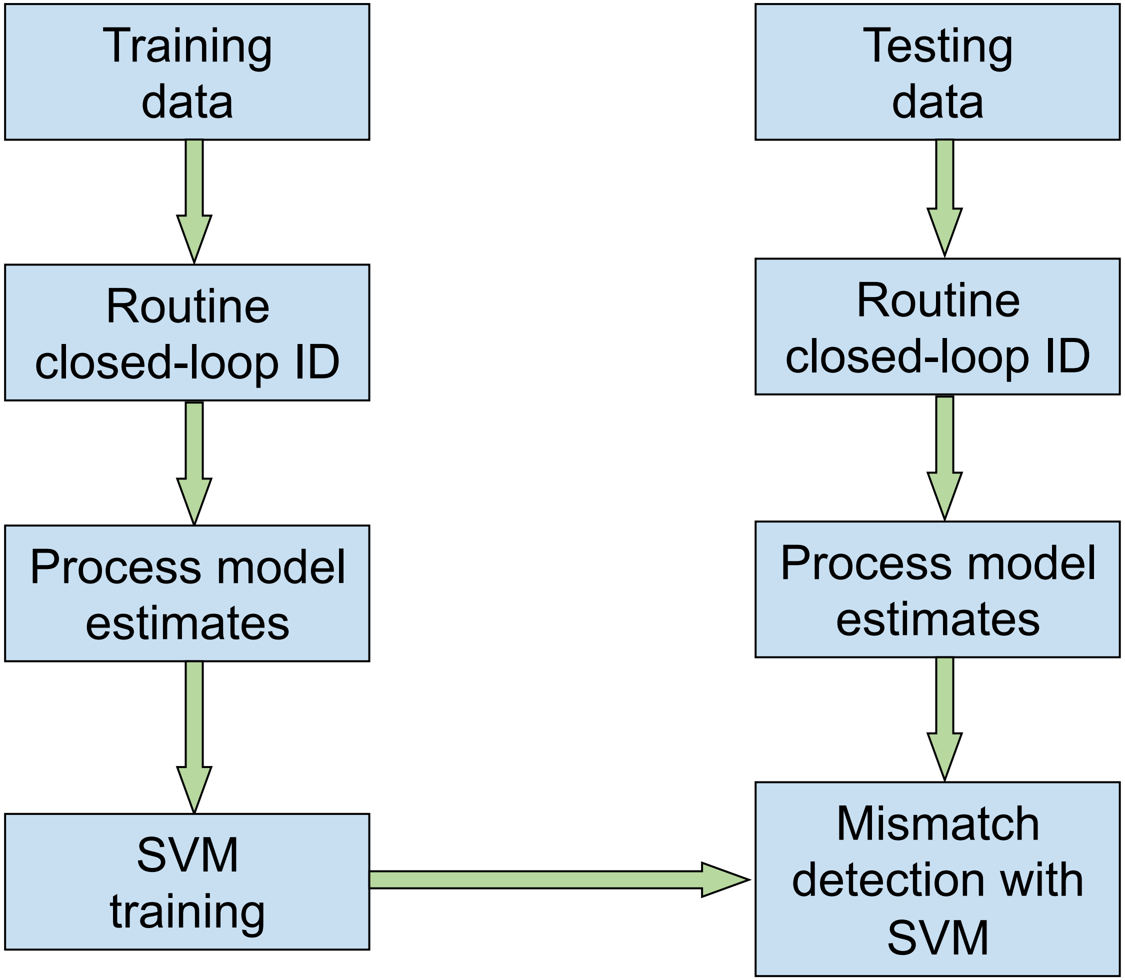
- The training and testing idea:



- MPM indicator: +1 means no mismatch; -1 means mismatch; 0 means SVM is under training.
- Actual algorithm works in moving window form.

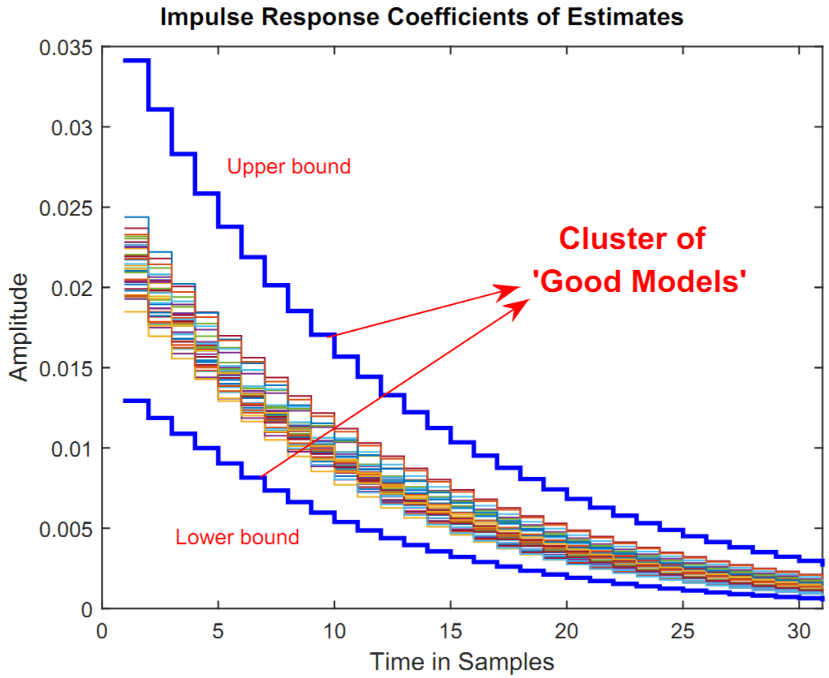
Model-Plant Mismatch Detection

- Mismatch detection logic flow

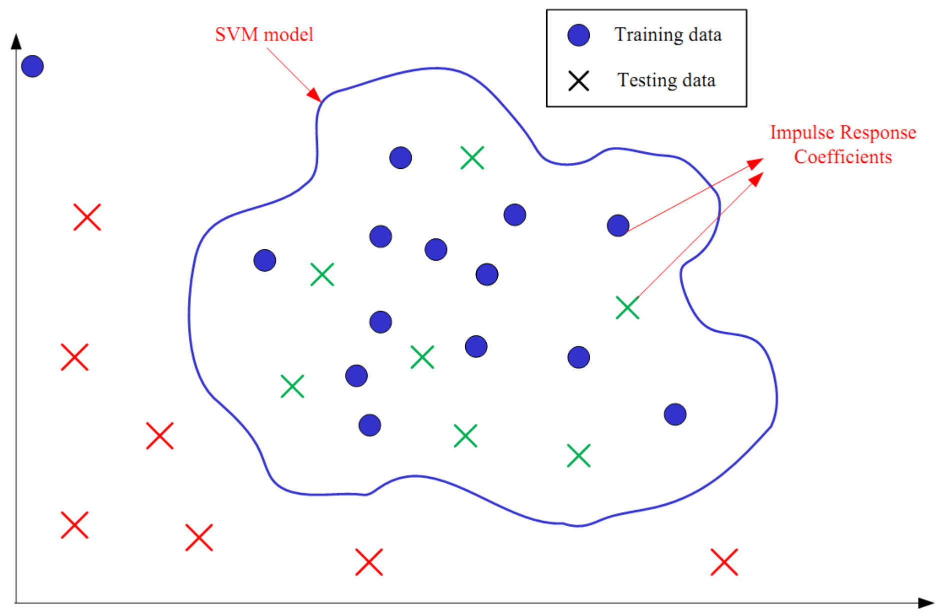


SVM Training and Testing

- Illustration of SVM training and testing idea



Cluster of impulse responses of process model estimates from 'good data'

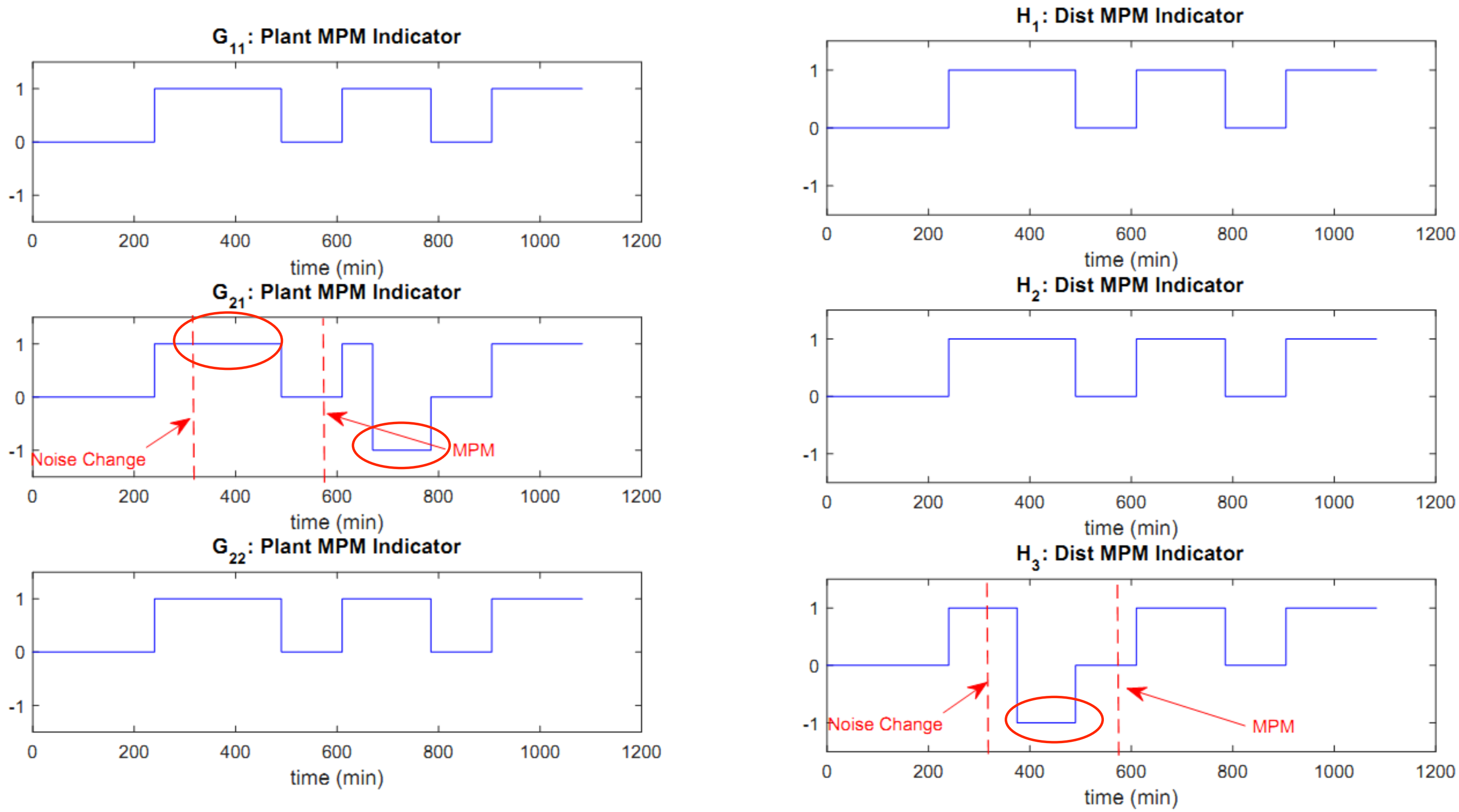


Mismatch detection is viewed as 'outlier detection'

- Can monitor MPM and noise change independently.

Mismatch Detection Example

- 3x3 lower triangular MD process with 3 MVs: stockflow, steam4, steam3, and 3 CVs: weight, press moisture and real moisture.



Optimal Input Design

- For ARX model structure

$$A(q^{-1},\theta)y(t) = B(q^{-1},\theta)u(t-d) + e(t)$$

- Covariance of parameter estimate $\hat{\theta}$ is

$$cov(\hat{\theta}) = (\Psi^T\Psi)^{-1} = R_u^{-1}$$

where Ψ is the regression matrix.

- Optimal input design is formulated as minimizing R_u^{-1}, or maximizing R_u, by choosing input signal

$$\max_u \; trace(R_u)$$

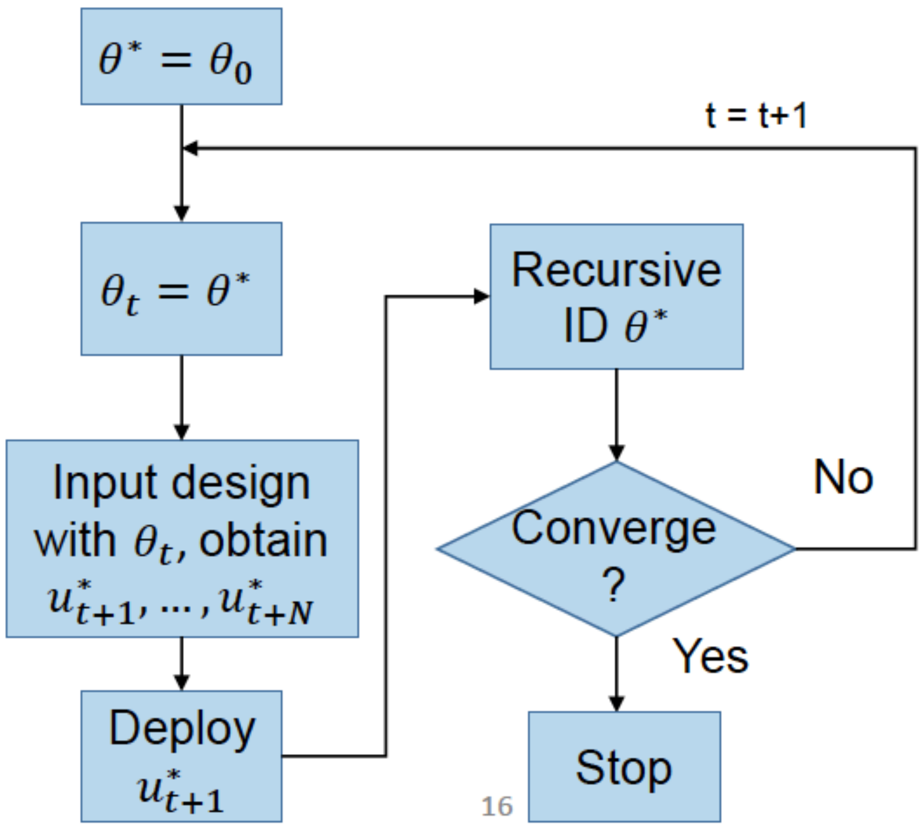
- It is shown that $R_u = U^T G U$, where U contains input signal, G is determined by process model information. The input design

$$\max_u \; trace(R_u)$$

$$s.t. \quad u_t \in \mathcal{U}, y_t \in \mathcal{Y}, \qquad t = 1, \ldots, N$$

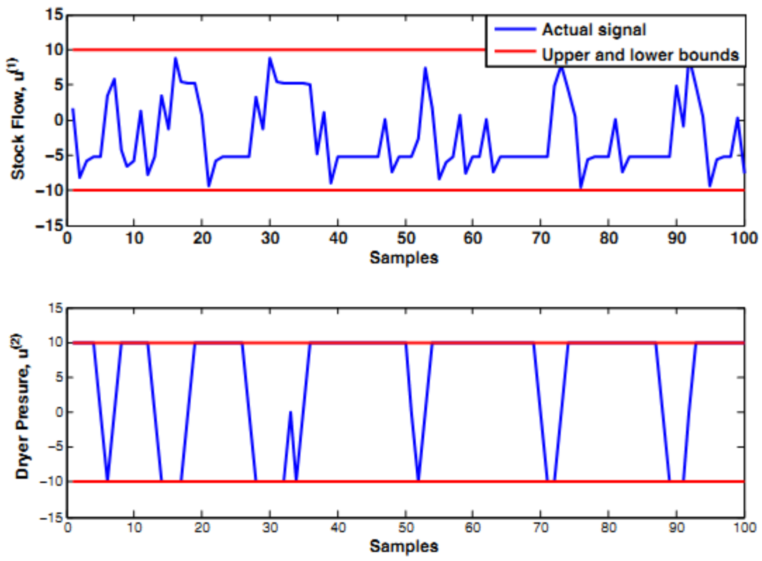
Moving Horizon Input Design

- Input design requires true parameter values that are not available.
- Cannot guarantee input and output within bounds due to the difference between initial and true parameter values.
- Moving horizon input design framework

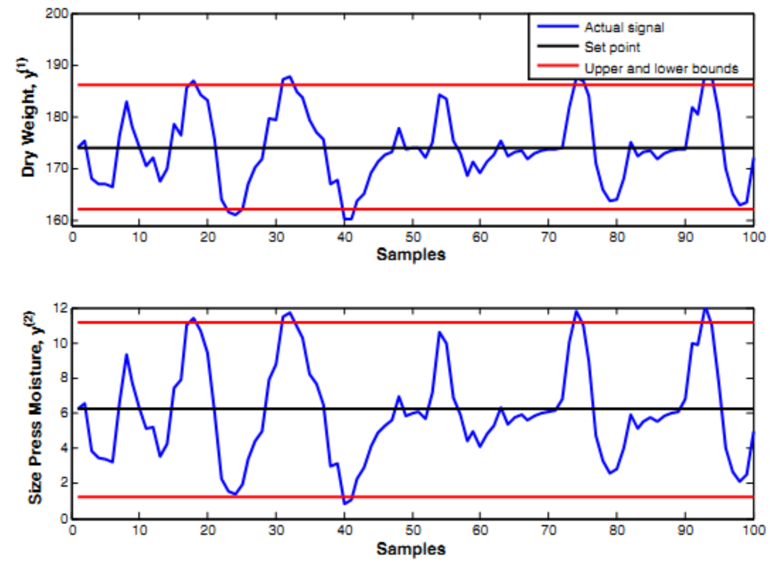


Optimal Input Design Example

- 2x2 lower triangular MD process, 2 CVs: dry weight, size press moisture, and 2 MVs: stock flow, dryer pressure



The designed excitation signal

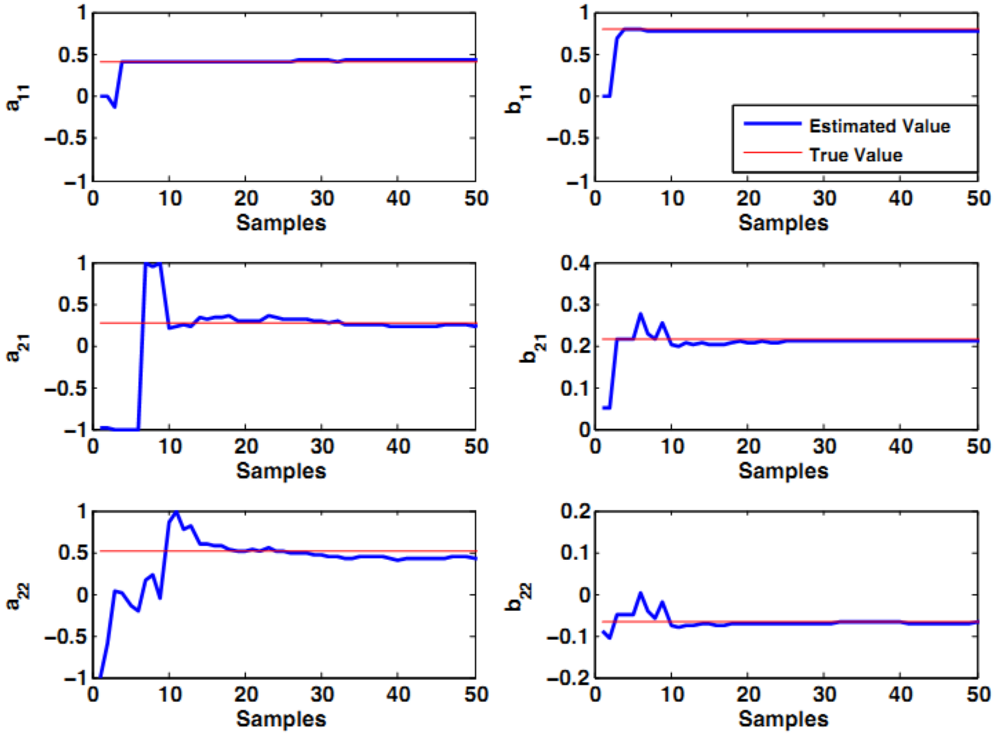


Closed-loop output profile

Honeywell

Optimal Input Design Example

- 2x2 lower triangular MD process, 2 CVs: dry weight, size press moisture, and 2 MVs: stock flow, dryer pressure



Recursive estimation of parameters

Summary

- Implemented the MVC benchmark to monitor controller performance for the MD process.
- Presented a novel closed-loop identification that can give consistent estimate for process model without requiring *a priori* knowledge on noise model;
- Proposed an SVM-based approach that can effectively detect mismatch and is not affected by noise model change.
- Designed an optimal input design scheme by maximizing the Fisher information matrix subject to a set of constraints on process input and output.

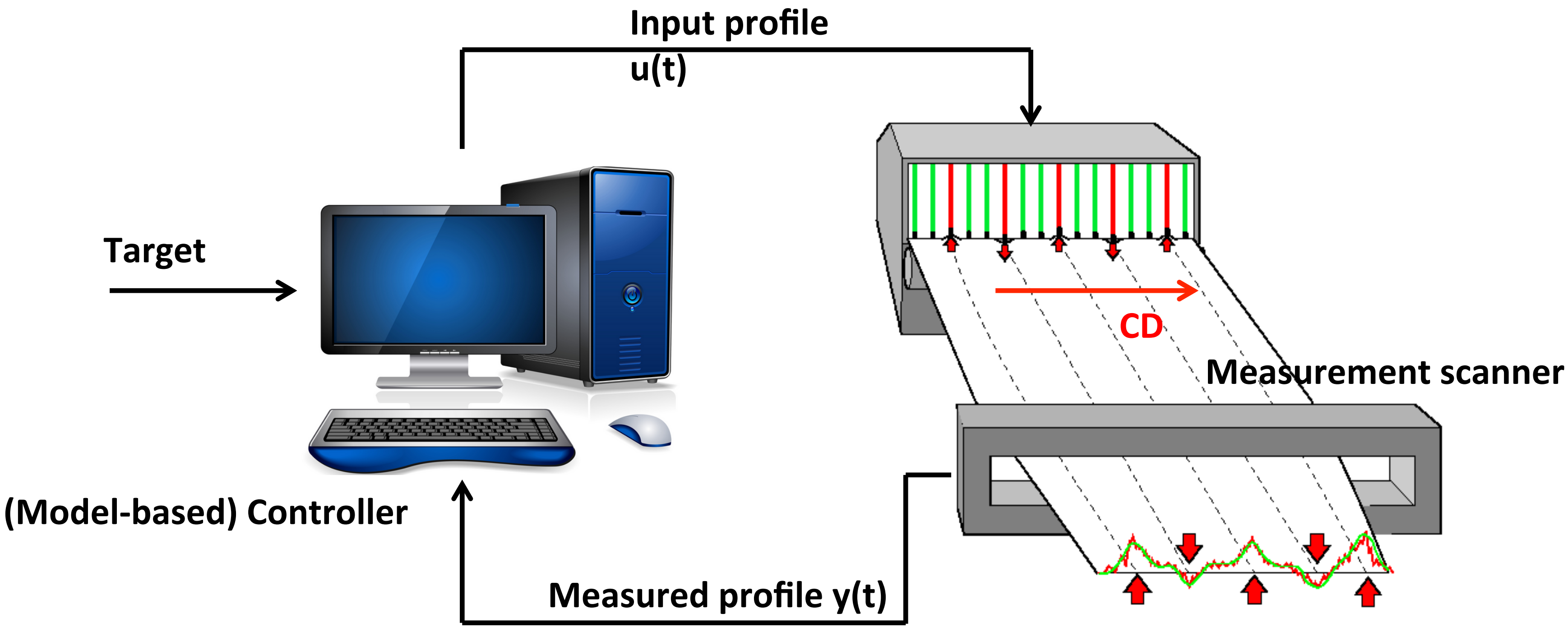
Adaptive Control for the Cross-Directional Process of Paper Machines

Outline

- CD process model and control
- Performance monitoring strategy
- Model-plant mismatch detection
- CD closed-loop input design
- Summary

CD Process Control

- Objective: keep paper sheet properties as flat as possible

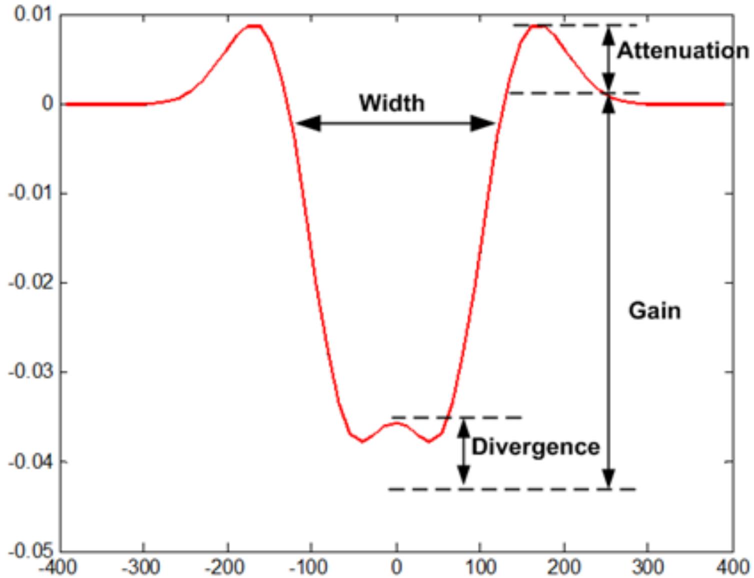


CD Process Model

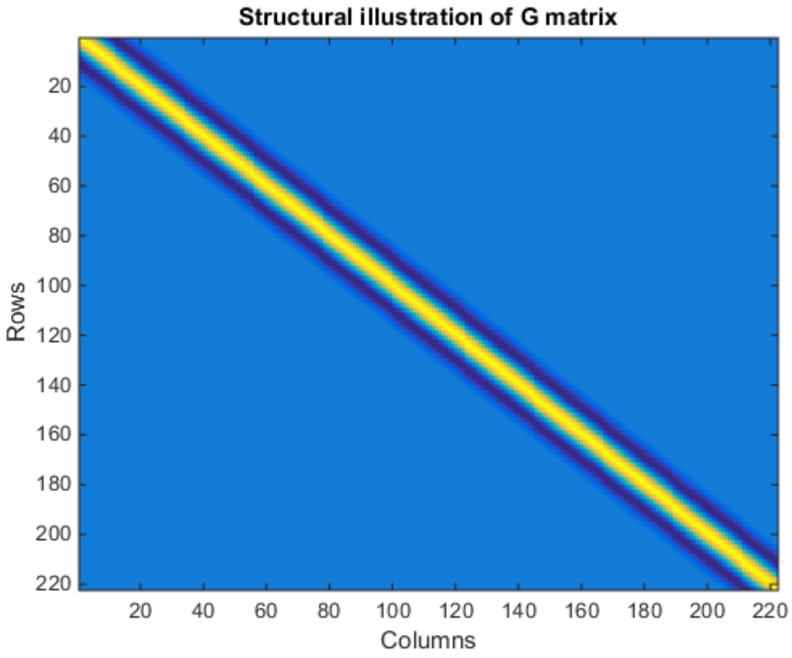
- Only consider the single array case

$$y(t) = g(z^{-1})Gu(t) + H(z^{-1})e(t)$$

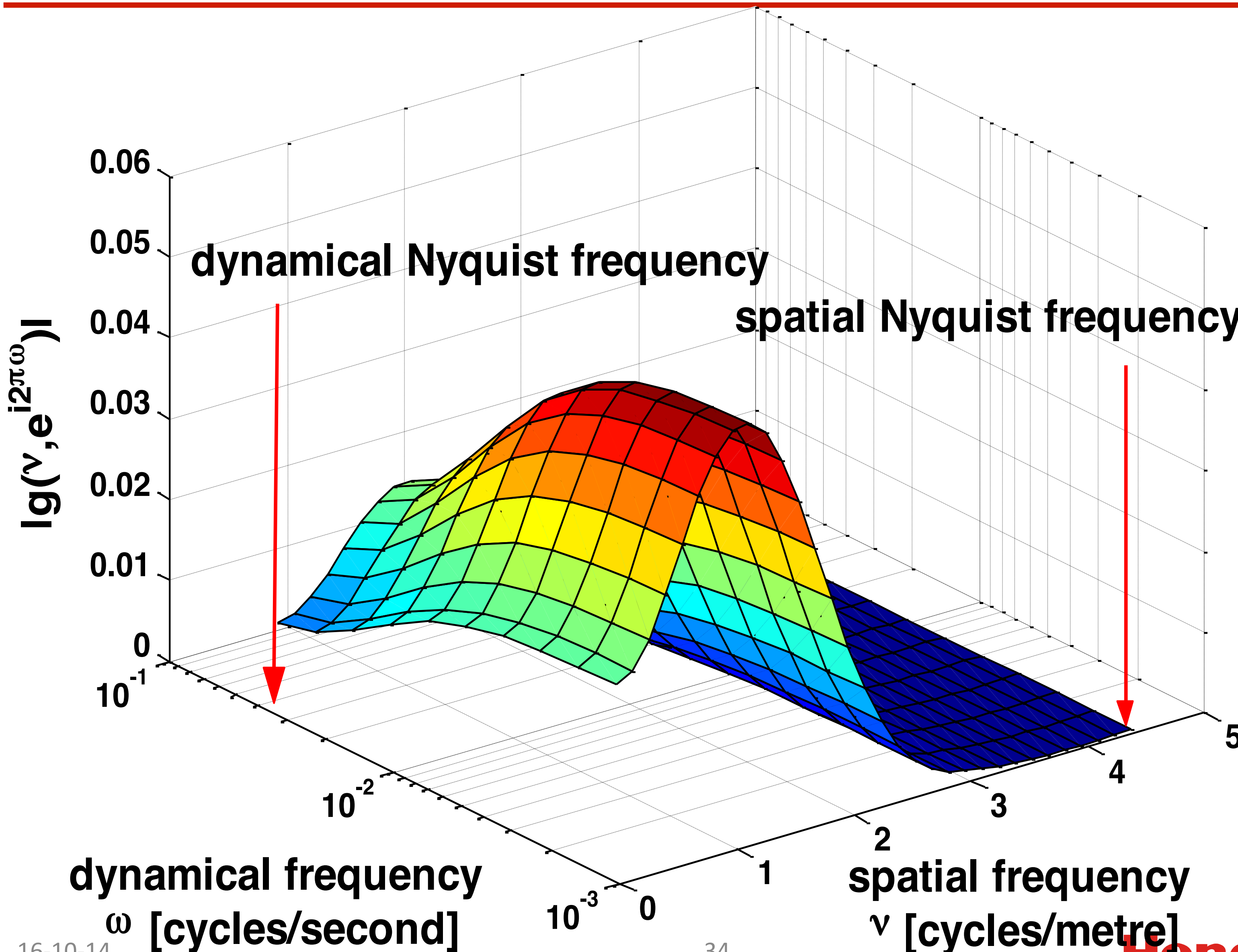
- Temporal parameter vector $\theta_T = [\tau, d]$. Spatial parameter vector is collected into $\theta_S = [\gamma, \xi, \beta, \alpha]$.



Single actuator spatial response



Structure of G matrix



0.06
0.05
0.04
0.03
0.02
0.01
0
dynamical Nyquist frequency
spatial Nyquist frequency
$|g(\nu, e^{i2\pi\omega})|$
10^{-1}
10^{-2}
10^{-3}
0
1
2
3
4
5
dynamical frequency
ω [cycles/second]
spatial frequency
ν [cycles/metre]

Honeywell

Performance Monitoring Strategy

- A performance index (PI) to assess control performance:

$$PI = \frac{trace(\Sigma_{benchmark})}{trace(\Sigma_{output})}$$

where $\Sigma_{benchmark}$ is the covariance of controller-invariant portion of output profile. Σ_{output} is the covariance of overall output profile.

- How to find controller-invariant parts from output profile?
  - Temporal direction: time-delay, unpredictable components;
  - Spatial direction: limited spatial bandwidth, uncontrollable parts.

Output Profile = Controller-dependent Part + Spatially-uncontrollable + Temporally-unpredictable

limited spatial bandwidth

temporal time-delay

Performance Monitoring Strategy

- Precisely, decompose output profile y(t) as:

$$y(t) = y_{p,c}(t) + \underbrace{y_{p,uc}(t) + y_{up,c}(t) + y_{up,uc}(t)}_{\text{controller-invariant}}$$

- Moving average (MA) form of controllable output profile

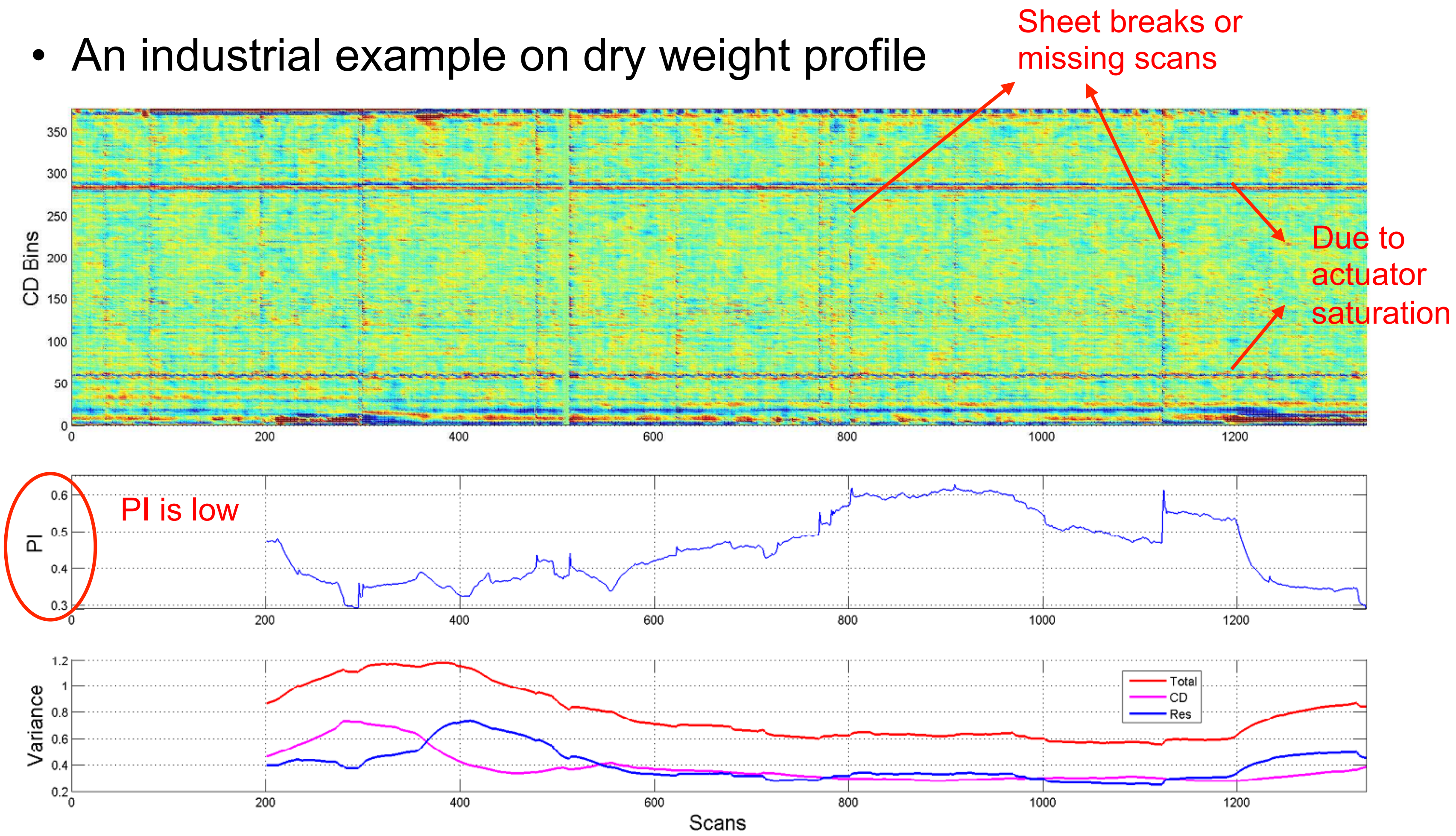
$$y_c(t) = \underbrace{f_0 e_c(t) + \cdots + f_{d-1} e_c(t-d+1)}_{\text{unpredictable due to time-delay}} + G_R(z^{-1}) e_c(t-d)$$

- Performance index η is defined as

$$\eta = \frac{trace\left[\sum_{i=0}^{d-1} f_i \Sigma_{e_c} f_i^T\right]}{trace\left[\Sigma_{y_c}\right]}$$

Performance Monitoring Example

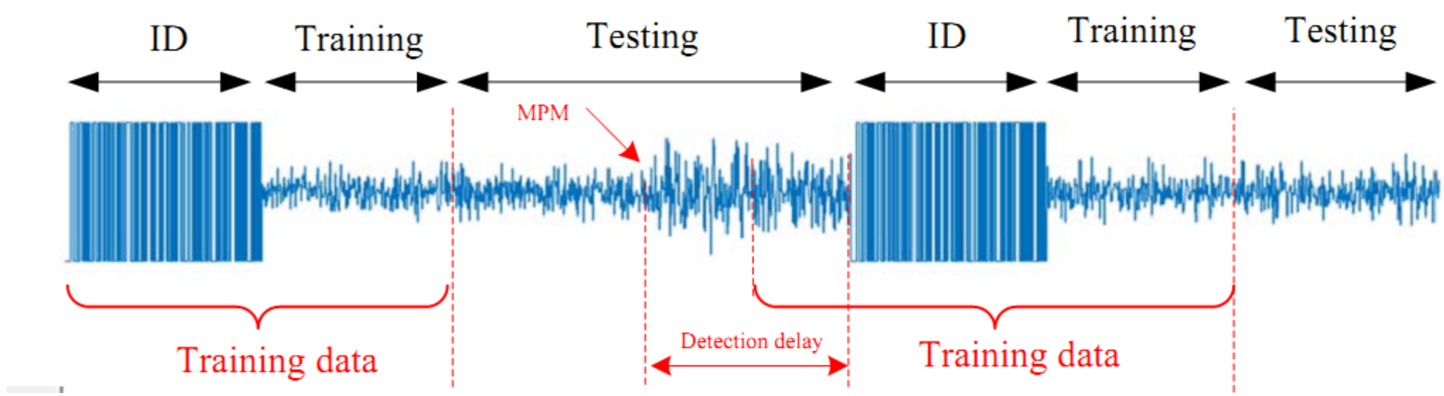
- An industrial example on dry weight profile



- PI is consistent with variance trend.

Model-Plant Mismatch Detection

- Various factors may drop performance index.
- It is not easy to discriminate mismatch from other causes.
- We hope to detect the mismatch with routine operating data where external excitations may not exist.
- Extend the SVM technique to the CD process.



- Two main building blocks: routine closed-loop ID and SVM tuning.

Optimal Input Design in Closed-loop

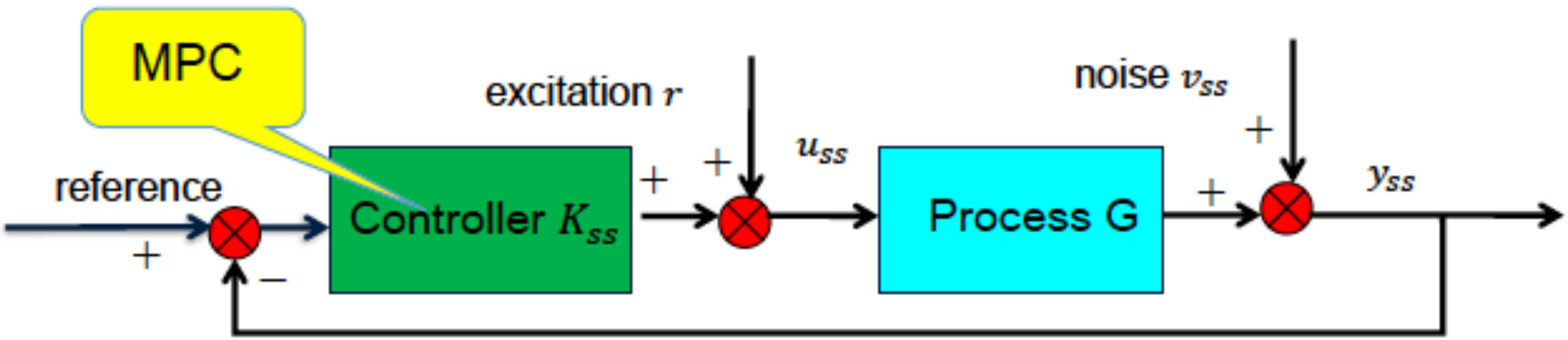


Fig. spatial input design scheme

- Focus on optimal input design for steady-state CD model *G*.
- Large number of inputs and outputs make it rather complex.
- Parsimonious noncausal modeling

$$y(x) = \frac{M(\lambda)M(\lambda^{-1})}{N(\lambda)N(\lambda^{-1})} r(x) + \frac{R(\lambda)R(\lambda^{-1})}{S(\lambda)S(\lambda^{-1})} e(x)$$

Optimal Input Design in Closed-loop

- Causal-equivalent representation

$$\tilde{y}(x) = \frac{M^2(\lambda^{-1})}{N^2(\lambda^{-1})} r(x) + \frac{R^2(\lambda^{-1})}{S^2(\lambda^{-1})} \tilde{e}(x)$$

- Input design based on causal-equivalent representation

$$\begin{aligned} &\underset{\Phi_r(\omega)}{\text{minimize}} && f(P_\theta^{-1}(\Phi_r(\omega))) \\ &\text{s. t.} && \underline{u} \leq u(t) \leq \bar{u} \\ & && \underline{y} \leq y(t) \leq \bar{y} \end{aligned}$$

covariance matrix

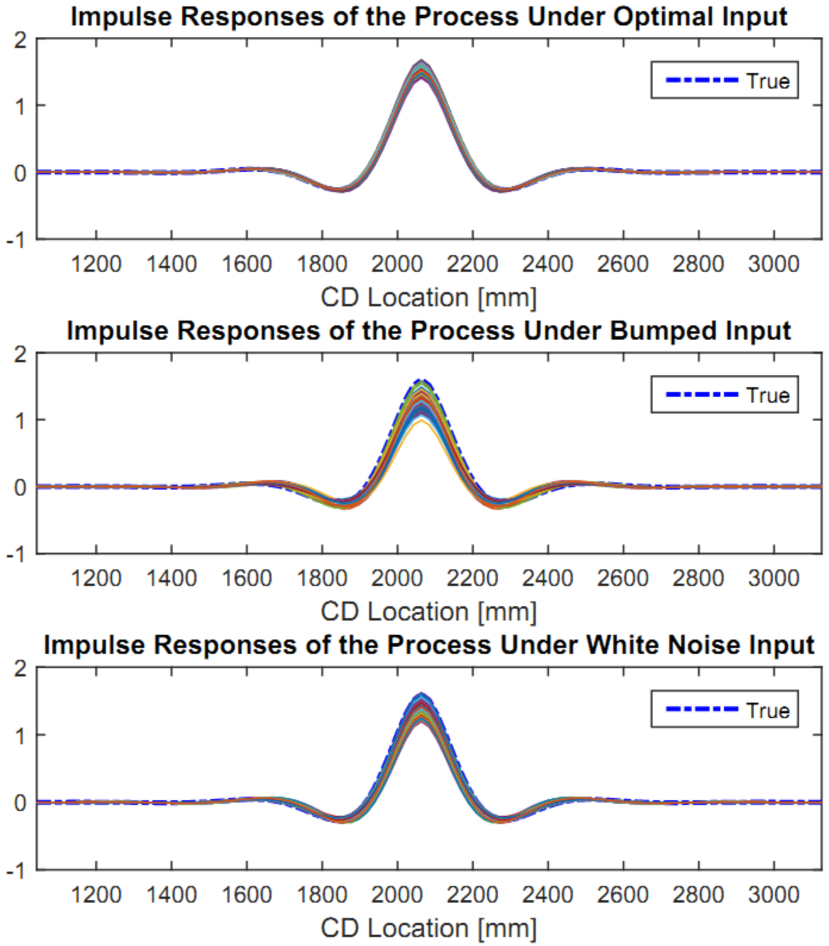
power constraints

- Finite parameterization of spectrum $\Phi_r(\omega)$ and reduce the problem into convex optimization.

Optimal Input Design in Closed-loop

- Comparison between optimal input, spatial bump perturbation and white noise input (same variance with optimal input).

  - 100 Monte-Carlo simulations under three dither signals
  - Closed-loop identification with data collected from every simulation
  - Estimates under optimal input have smallest variance
  - Estimates under bump perturbation have largest variance



References - I

- Q. Lu, M.G. Forbes, R.B. Gopaluni, P.D. Loewen, J.U. Backstrom, and G.A. Dumont. Performance assessment of cross-directional control for paper machines. IEEE Transactions on Control Systems Technology, 2016.
- Q. Lu, L.D. Rippon, R.B. Gopaluni, M.G. Forbes, P.D. Loewen, J.U. Backstrom, and G.A. Dumont. Cross-directional controller performance monitoring for paper machines. American Control Conference, 2015.
- Q. Lu, L.D. Rippon, R.B. Gopaluni, M.G. Forbes, P.D. Loewen, J.U. Backstrom, and G.A. Dumont. A closed-loop ARX output-error identification method for industrial routine operating data. 2016.
- Q. Lu, R.B. Gopaluni, M.G. Forbes, P.D. Loewen, J.U. Backstrom, and G.A. Dumont. Identification of symmetric noncausal processes: cross-directional response modeling in paper machines. 2016.
- Q. Lu, R.B. Gopaluni, M.G. Forbes, P.D. Loewen, J.U. Backstrom, and G.A. Dumont. Model-plant mismatch detection with support vector machines. 2016.

References - II

- Q. Lu, R.B. Gopaluni, M.G. Forbes, P.D. Loewen, J.U. Backstrom, and G.A. Dumont. Noncausal modeling and closed-loop optimal input design for cross-directional processes of paper machines. 2016.
- Q. Lu, L.D. Rippon, P.D. Loewen, R.B. Gopaluni. Adaptive control of paper machines. Technical report, 2016.
- M. Yousefi, Q. Lu, R.B. Gopaluni, P.D. Loewen, M.G. Forbes, G.A. Dumont, J.U. Backstrom. Detecting model-plant mismatch without external excitation. American Control Conference, 2015.
- M. Yousefi, L.D. Rippon, M.G. Forbes, R.B. Gopaluni, P.D. Loewen, G.A. Dumont, J.U. Backstrom. Moving-horizon predictive input design for closed-loop identification. AdChem, 2015.
- M. Yousefi, M.G. Forbes, R.B. Gopaluni, G.A. Dumont, J.U. Backstrom, A. Malhotra. Sensitivity of controller performance indices to model-plant mismatch: an application to paper machine control. American Control Conference, 2015.