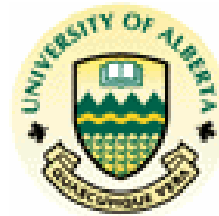


MPC Monitoring: Detection and Diagnosis of Model Errors



Abhijit Badwe¹ and Rohit Patwardhan²

¹Department of Chemical and Materials Engineering
University of Alberta

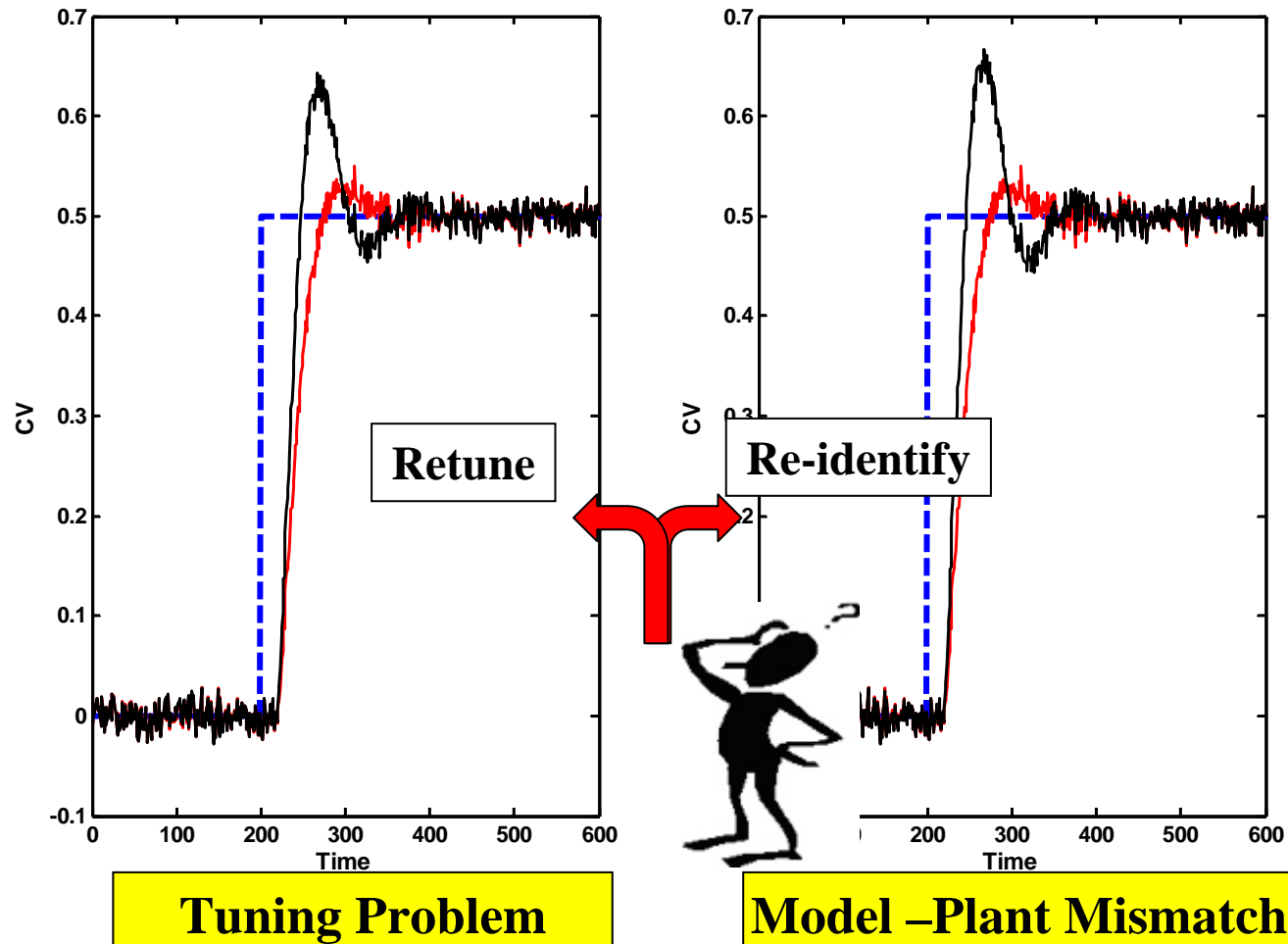
²Matrikon Inc, Edmonton, Canada

Credits: Bruce Wilson and Foon Szeto (Suncor Energy Inc.)

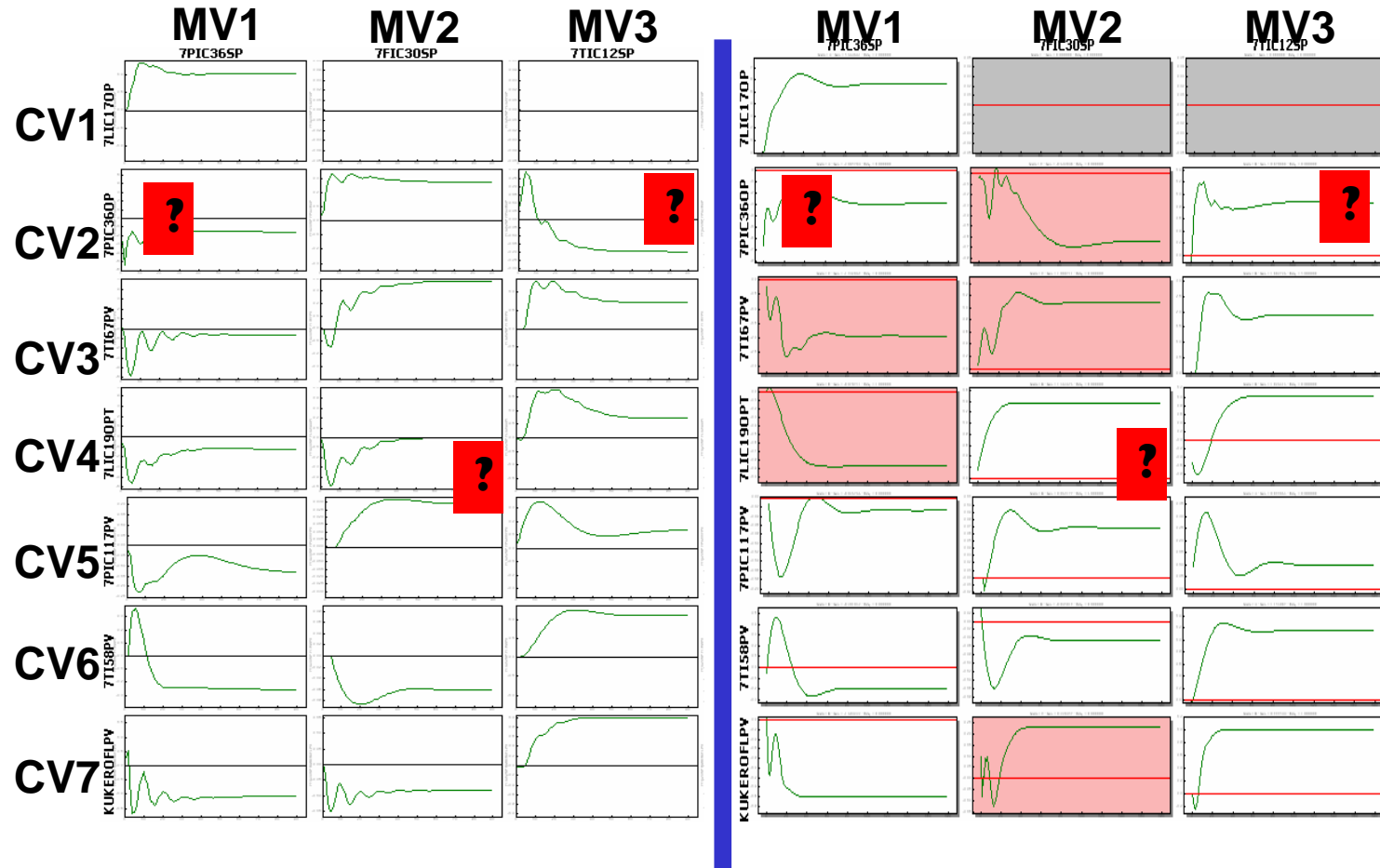
-
1. Introduction
 2. Motivation
 3. Assessing the need for re-identification
 4. Detection and Isolation of Mismatch
 5. Case Studies
 6. Concluding Remarks

- MPC performance is affected by model quality
- Model quality is influenced by changes in the plant and/or operating conditions
- Online model maintenance:
 - Monitoring of model quality
 - Mismatch detection and isolation
 - Assessment of need for re-identification
 - Only update the model if necessary
 - Identification under closed-loop
- Performance after maintenance

Motivation: Retune or Re-identify?

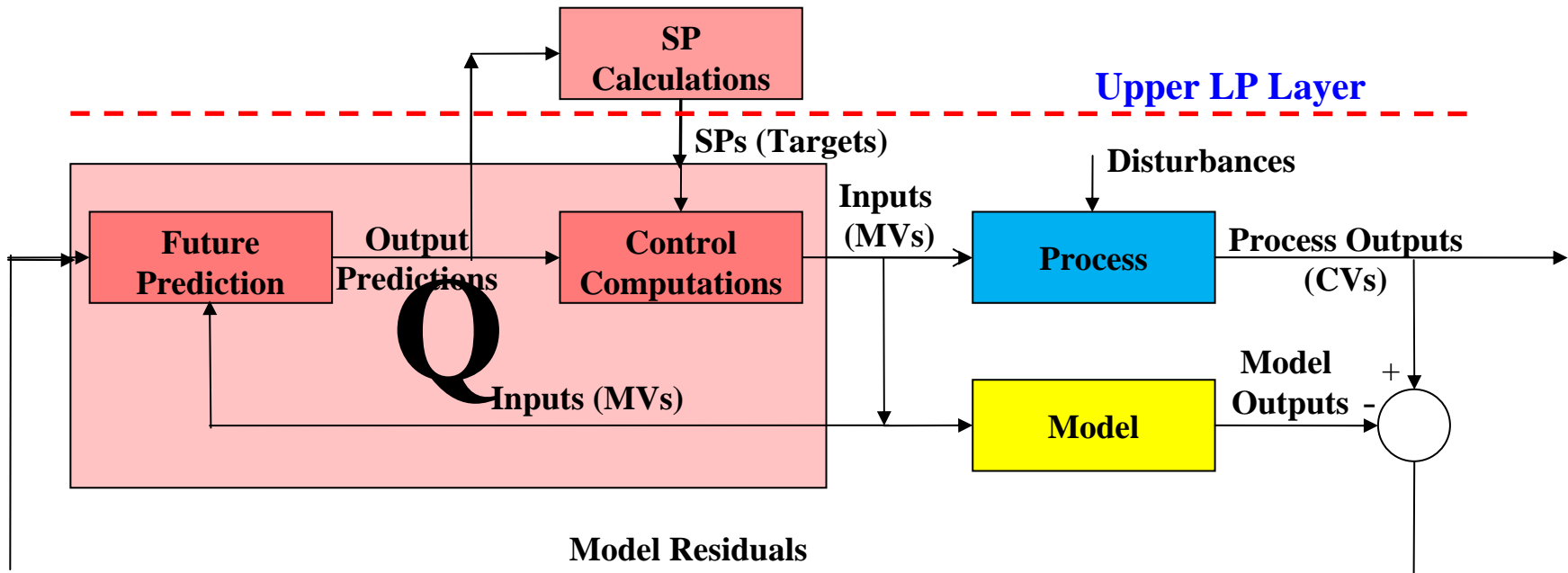


Motivation: Locate Significant MPM



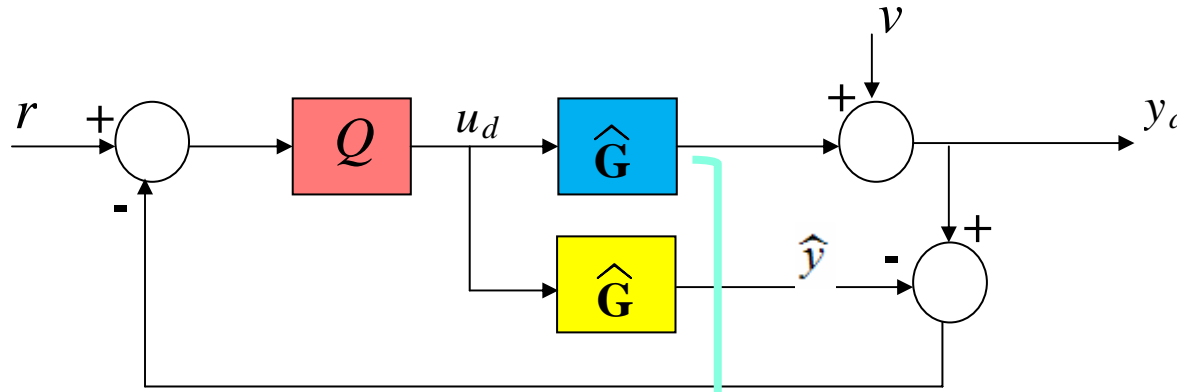
MPM – Effect on controller performance

- Do we need to worry about MPM?
- If yes, when?
- Can we quantify the effect of MPM on performance?
- A measure of degradation in controller performance – **How far is the achieved performance from the designed performance?**
- **Relate MPM and this measure**



Internal Model Control (IMC) Structure

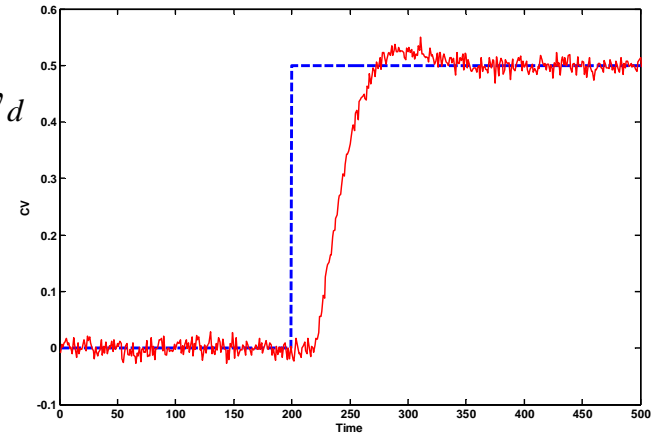
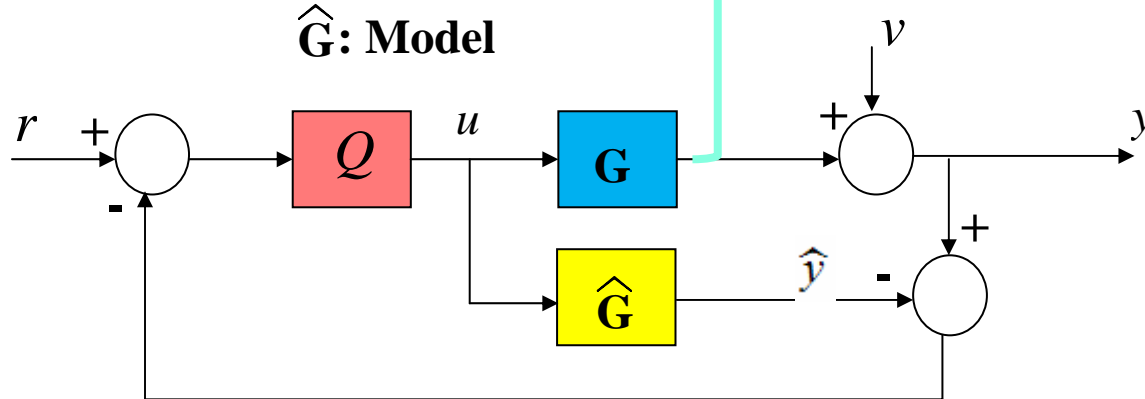
Designed and Achieved Performances



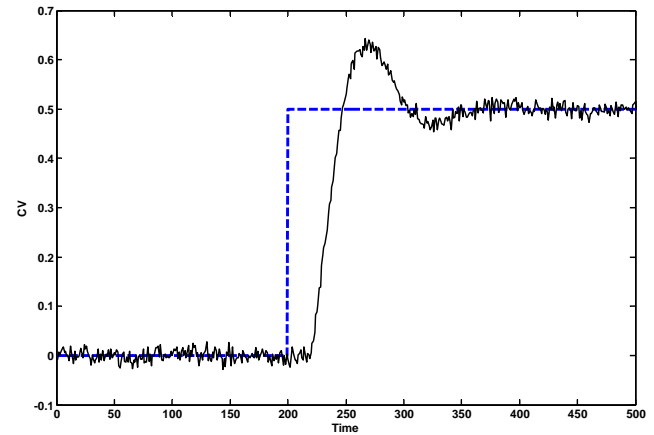
G : Actual Process

\hat{G} : Model

$$\Delta = G - \hat{G}$$



Designed Performance



Achieved Performance

Important Closed-loop Term - 1

$$\text{Achieved Performance} = \left[\frac{1}{1+\Delta Q} \right] \text{Designed Performance}$$

$r - y_{\text{achieved}}$

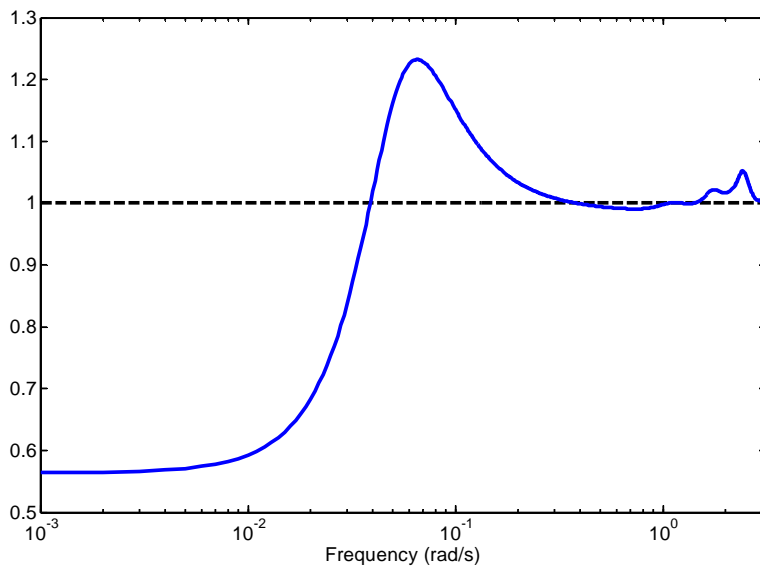
$(\text{MV})_{\text{achieved}}$

$(\text{Sensitivity})_{\text{achieved}}$

$r - y_{\text{designed}}$

$(\text{MV})_{\text{designed}}$

$(\text{Sensitivity})_{\text{designed}}$



$$\left\| \frac{1}{1+\Delta Q} \right\|_{\infty} > 1 \Rightarrow \text{Achieved is worse than designed}$$

- Indicates presence of MPM

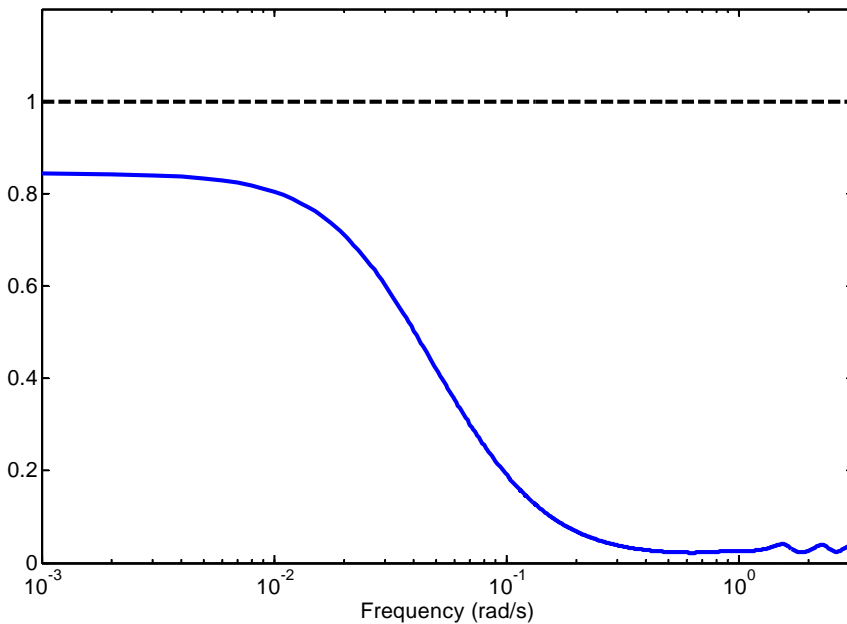
OR

- MPM 'mishandled' by controller

Important Closed-loop Term - 2

$$\|\Delta Q\|_{\infty} < 1$$

$\|\Delta Q\|_{\infty} \Rightarrow$ Measure of Robustness

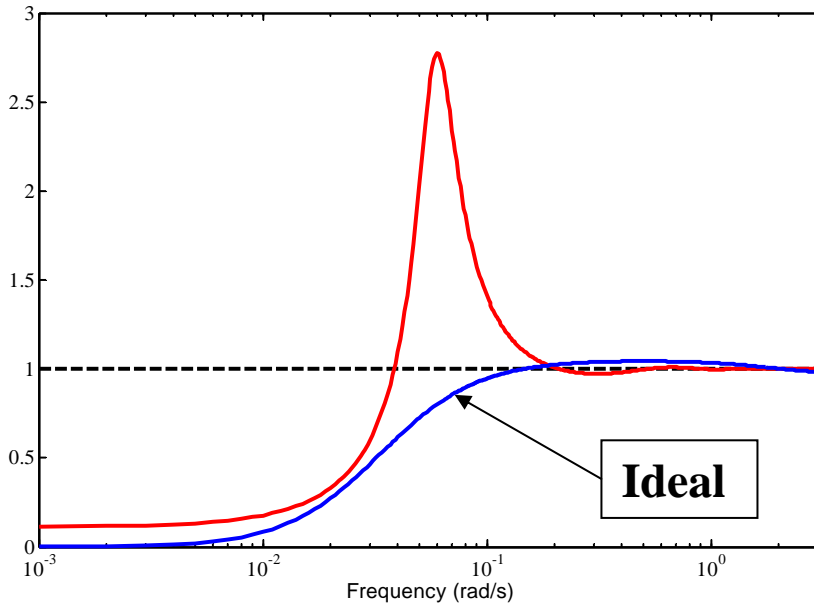


- Sufficient condition for stability
- Smaller the value, the more robust is the closed-loop to the current MPM

Important Closed-loop Term - 3

$$S_{\text{designed}} = \left[1 - \hat{G}Q \right] \quad \text{Designed Sensitivity}$$

Sensitivity: Closed-loop relationship between the CV and the disturbance



- **A measure of the designed performance**
- **Depends on controller tuning**
- **A large peak (> 2) indicates poor designed performance – Issues with tuning**

Key Observations

- All terms can be estimated from routine operating data – SPs, CVs and model residuals are required.
- Variability: $\frac{\text{var}(e_{ach})}{\text{var}(e_{des})} \leq \left\| \frac{1}{1+\Delta Q} \right\|_{\infty}^2$
- Degraded performance:

$\left\ \frac{1}{1+\Delta Q} \right\ _{\infty}$	$\ \Delta Q\ _{\infty}$	$\ S_{designed}\ _{\infty}$	Diagnosis	Recommendation
≈ 1	≈ 0	> 2	Tuning problem	Retune
> 1	≥ 1	> 2	Severe MPM	Retuning may help
> 1	≥ 1	< 2	Severe MPM	Re-identify
≈ 1	≈ 0	< 2	Disturbances	

Illustrative Example: SISO MPC

Plant:

$$G = \frac{4e^{-25s}}{50s+1}$$

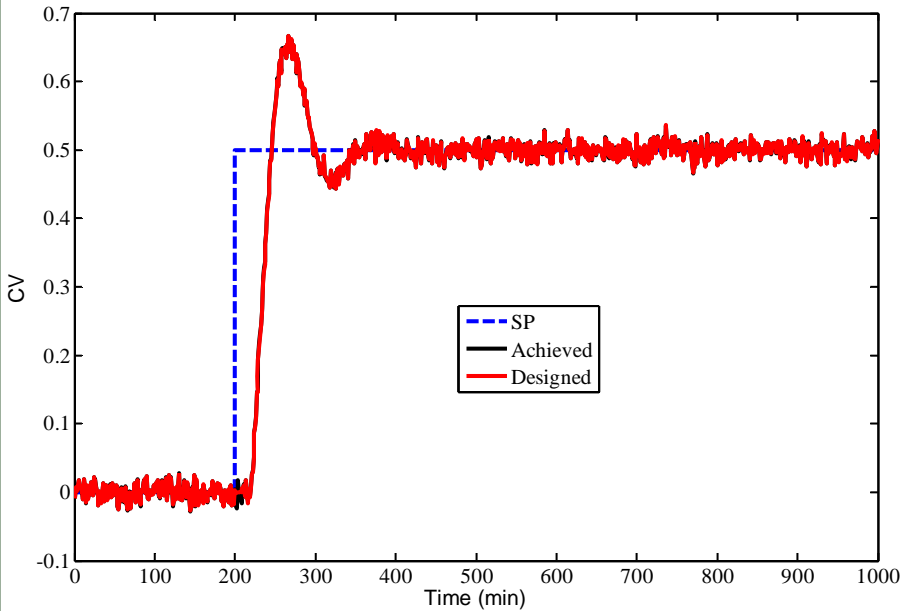
Controller:

MPC : Design based on the model G

Prediction Horizon	40
Control Horizon	3
Error Weight	1

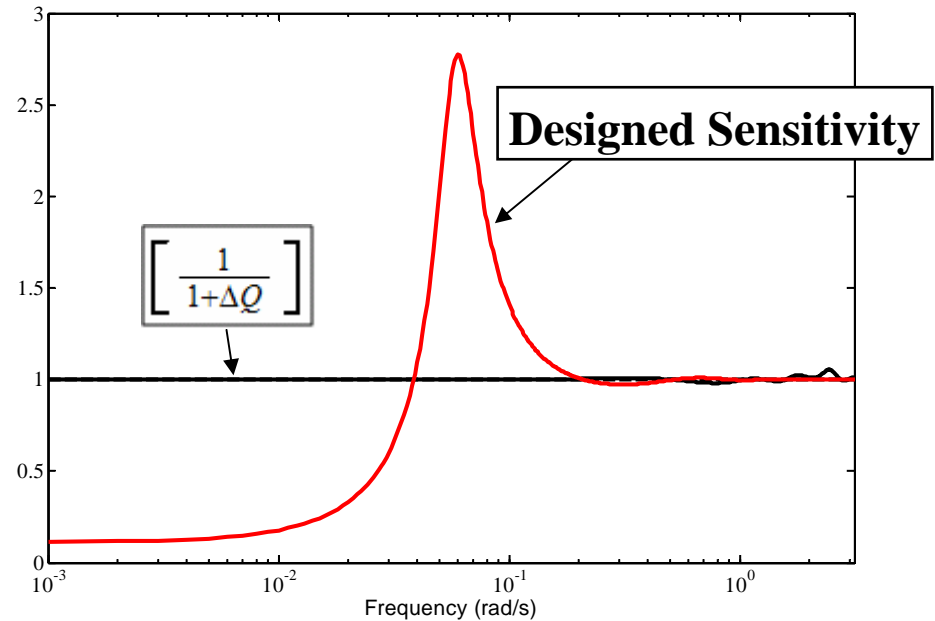
Disturbance: Integrated white noise of std. deviation 0.005

Case-1: Tuning Problem, Perfect Model



Simulation

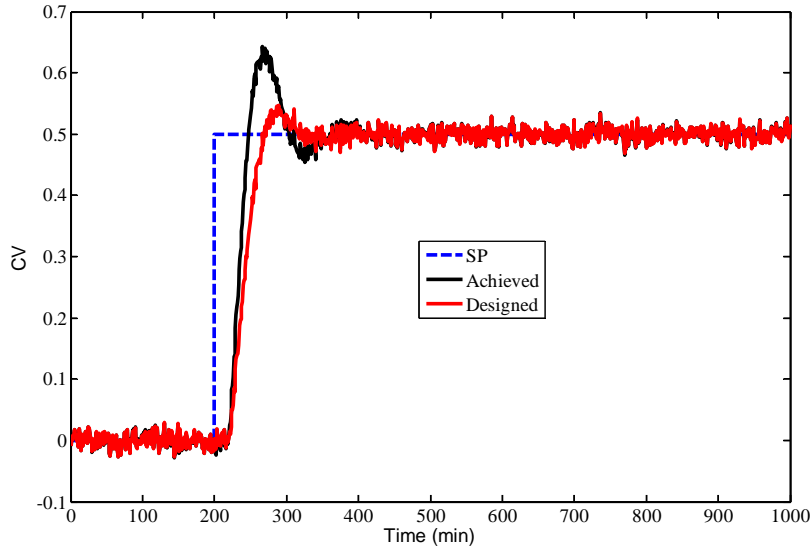
- Aggressively tuned controller
- Model is perfect



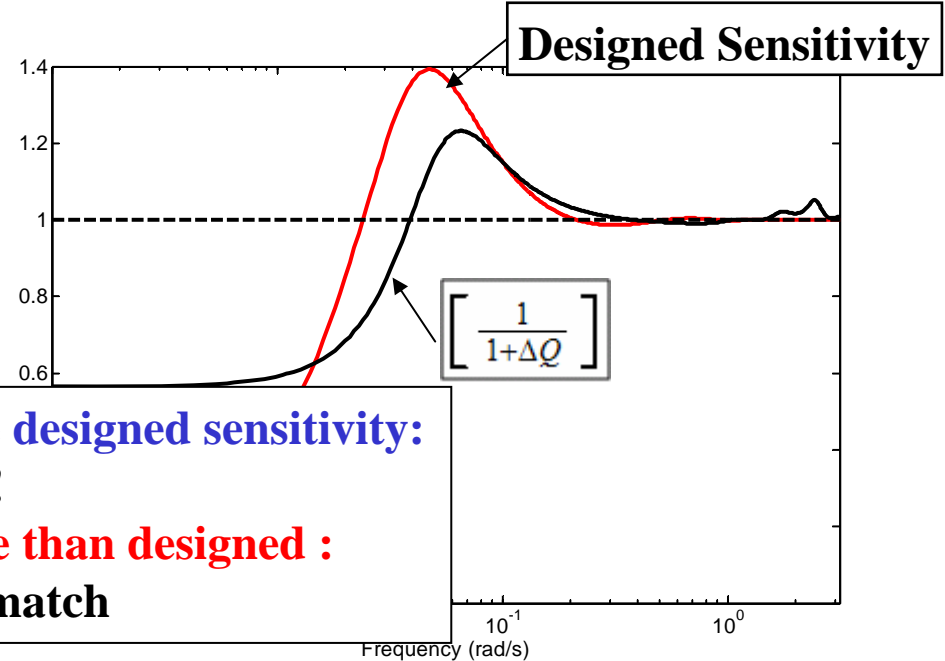
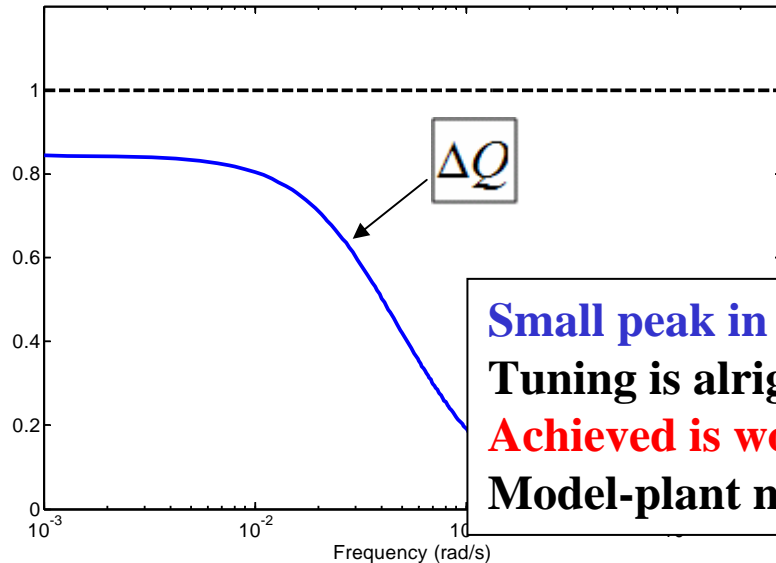
Achieved is as good as designed :
No model-plant mismatch

Peak in the designed sensitivity:
Tuning Problem

Case-2: Good Tuning, Model-Plant Mismatch

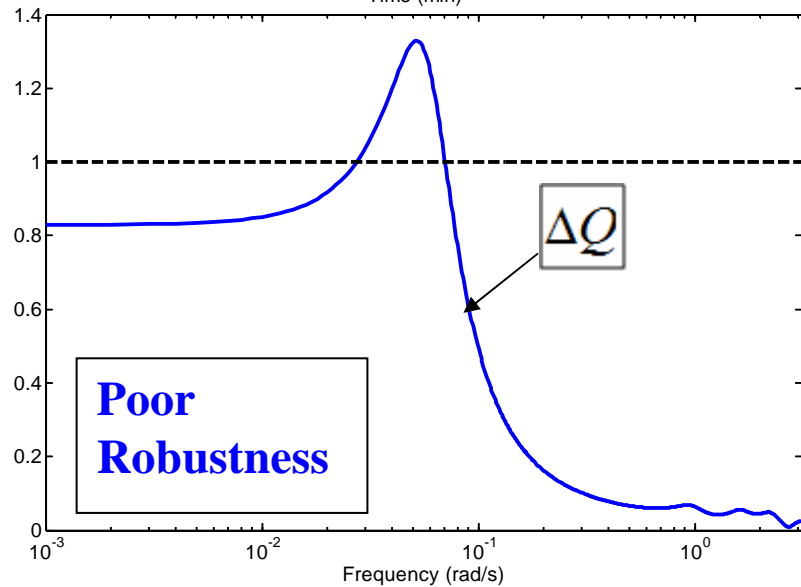
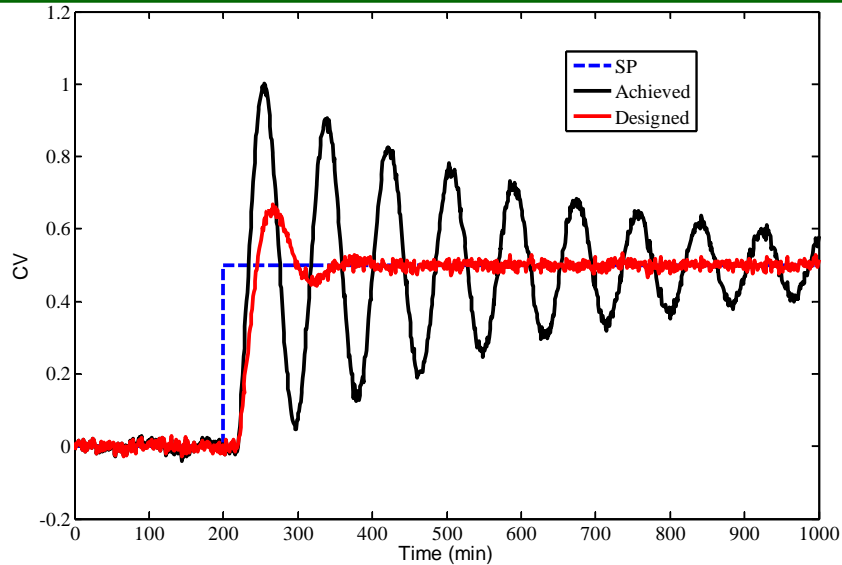


- Simulation**
- Well-tuned controller
 - **Model-plant mismatch: *Gain is Underestimated by 50%***



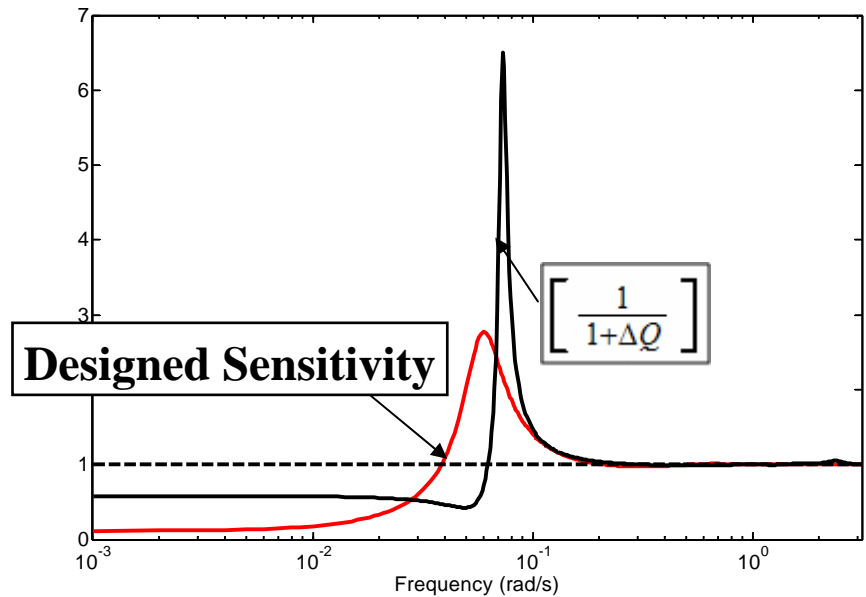
**Small peak in the designed sensitivity:
Tuning is alright!
Achieved is worse than designed :
Model-plant mismatch**

Case-3: Bad Tuning, Model-Plant Mismatch

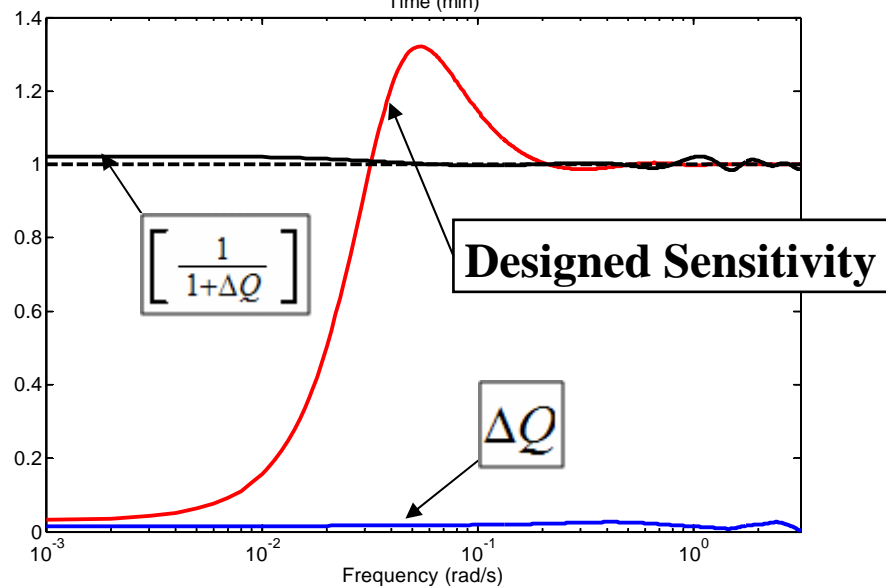
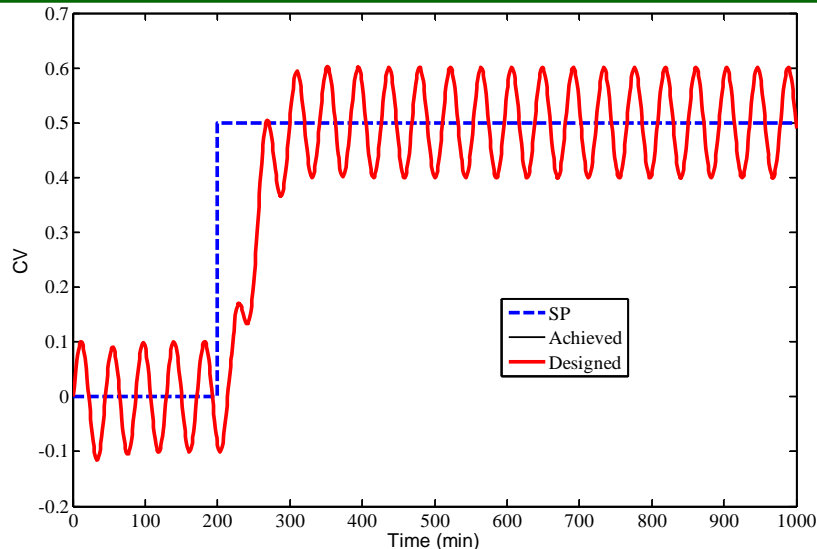


Simulation

- **Aggressive controller**
- **Model-plant mismatch: *Gain is Underestimated by 50%***



Case-4: Degradation due to disturbance



Simulation

- Well tuned controller
- Perfect Model
- Oscillatory disturbance in the process

Small peak in the designed sensitivity:

Tuning is alright!

Achieved is as good as designed :

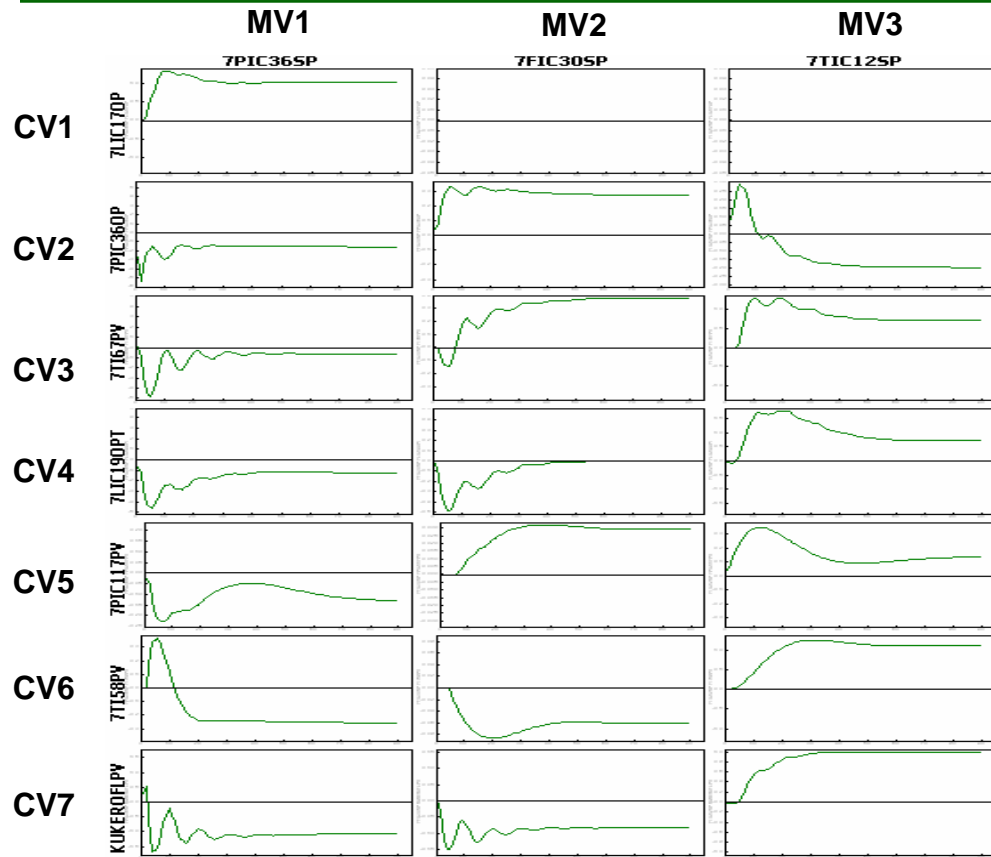
Model is perfect!

Degradation in performance is due to disturbance.

Summary

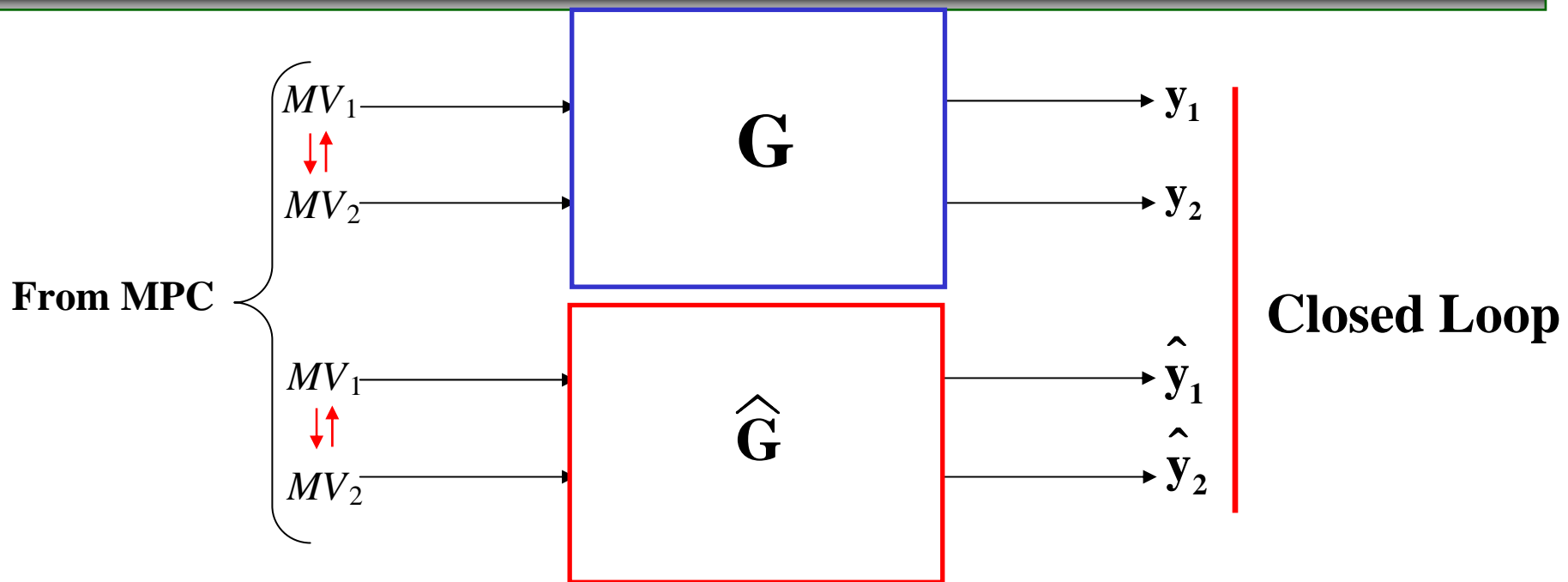
Case	$\frac{\text{var}(e_{ach})}{\text{var}(e_{des})}$	$\left\ \frac{1}{1+\Delta Q} \right\ _{\infty}$	$\ \Delta Q\ _{\infty}$	$\ S_{designed}\ _{\infty}$
Tuning problem	0.99	1.015	0.005	2.75
MPM	1.26	1.21	0.84	1.4
MPM + Tuning problem	6.10	6.46	1.32	2.77
Disturbances	1.03	1.02	0.002	1.36

MIMO Process - Location of MPM



Isolate that part/subsystem where model-plant mismatch is significant

MPM in MPC



Correlated

$$e_1 = \Delta_{11}MV_1 + \Delta_{12}MV_2 + v_1$$

$$e_2 = \Delta_{21}MV_1 + \Delta_{22}MV_2 + v_2$$

$$G - \hat{G} = \begin{bmatrix} \Delta_{11} & \Delta_{12} \\ \Delta_{21} & \Delta_{22} \end{bmatrix}$$

MPM with MPC - Issues

- Correlations amongst the MVs
- Correlated MVs confound regular correlation analysis between model residuals and MVs – Misleading information regarding presence (or absence) of significant mismatch
- Absence of setpoint activity – $\mathbf{e} = -\mathbf{Q}^{-1}\mathbf{u}$
 - Detection of mismatch is not possible
 - In practice, setpoint activity is quite common

Problem and Approach

- **Problem:** A methodology for the detection and isolation of plant-model mismatch for MPC using closed-loop data.
- **Approach:** Analysis of partial correlations between the model residuals and the inputs.

Partial Correlations - Introduction

- Partial correlation analysis is a method used to describe the relationship between two variables whilst taking away the effects of other variables.
- Extensively used in social sciences.
- Generally linear regression is used to de-correlate variables.

Partial Correlation Analysis for Problem at hand

- We wish to analyze partial correlations in a dynamic sense because the variables under consideration (MVs and model residuals) are time series variables.
 - ✓ Use lagged variables
- Disturbances may confound the analysis of partial correlations
 - ✓ Replace linear regression by PEM based models

Methodology based on Partial Correlations

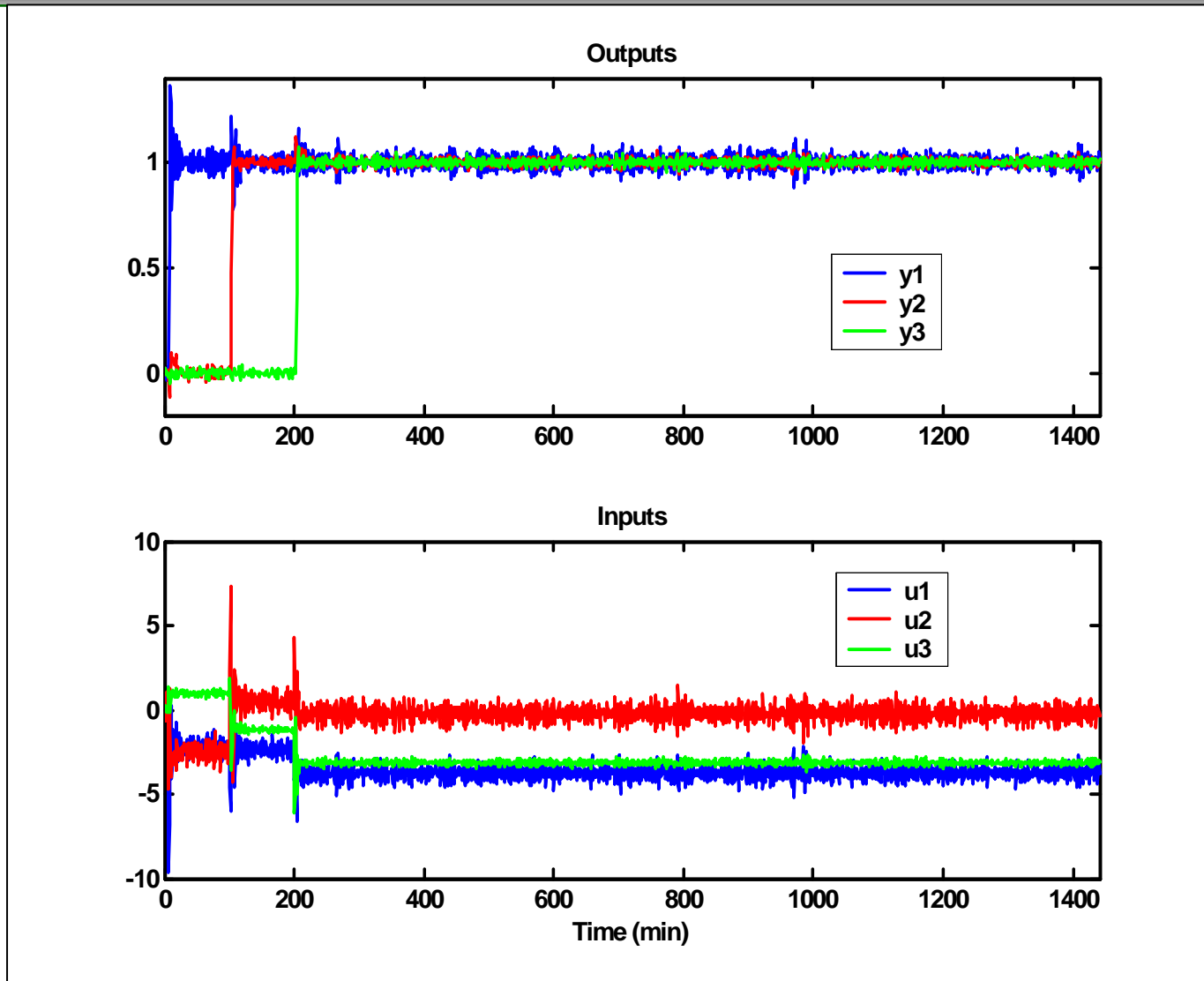
1. Choose data (model residuals and MVs) from the period where there is **sufficient setpoint excitation** in the process.
2. Identify relationship between MV_i and rest of the MVs and evaluate associated prediction error, E_{MV_i} .
3. Identify relationship between residual, e_j and all MVs except MV_i and evaluate associated error, E_{e_j} .
4. Evaluate correlation between E_{MV_i} and E_{e_j} – Large correlation indicates significant mismatch in channel MV_i - CV_j .

Case Study 1: Simulations on a 3x3 system ²⁶

- Simulation of 3 CVs X 4 MVs example
- MPC controller parameters:
 - Prediction Horizon = 30
 - Control Horizon = 10
 - Sampling Time = 1 min
 - All CVs are equally weighted
 - All MVs are equally weighted with move suppression factor = 0 or 1
 - MV4 is constrained at its lower limit – 3CVs X 4MV controller
- Each MV is a setpoint to a PID loop

Case Study 1 – Gain mismatch

- MV1- CV1,CV2 gains underestimated by 50%
- Full and partial correlations analyzed
- Channels corresponding to residual-MV pairs with significant partial correlations contain mismatch



Case Study-1: Gain Mismatch – Full and partial correlation 29 coefficients

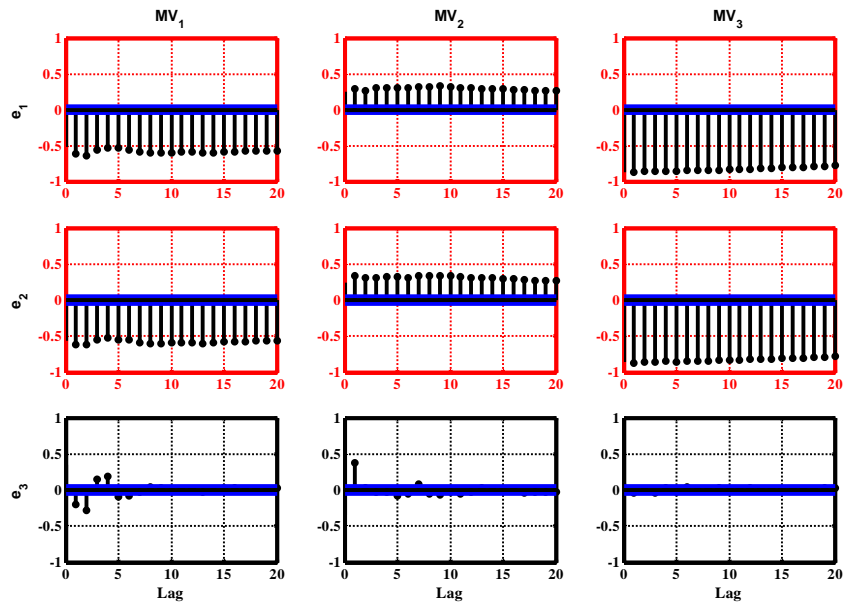
Correlation coefficients between residuals and inputs

	u1	u2	u3
e1	-0.62 (0)	0.28 (0)	-0.88(0)
e2	-0.62 (0)	0.28 (0)	-0.88(0)
e3	-0.006 (0.81)	-0.02 (0.42)	0.002 (0.92)

Partial correlation coefficients between residuals and inputs

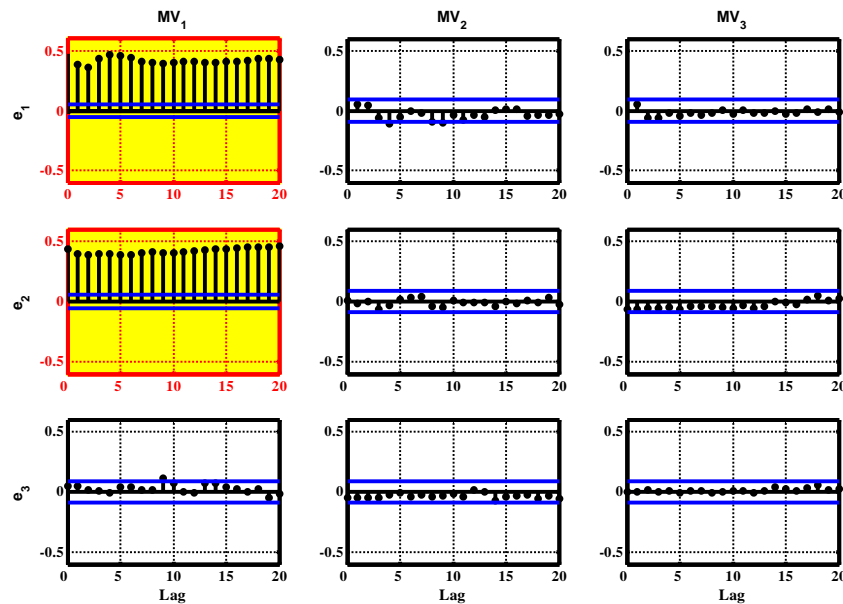
	u1	u2	u3
e1	0.15 (0)	-0.01 (0.57)	0.08 (0.16)
e2	0.38 (0)	-0.02 (0.33)	-0.04 (0.13)
e3	0.001 (0.97)	-0.01 (0.61)	-0.02 (0.48)

Mismatch correctly located in channels u1-y1,y2



Partial correlation plots

Full correlation plots



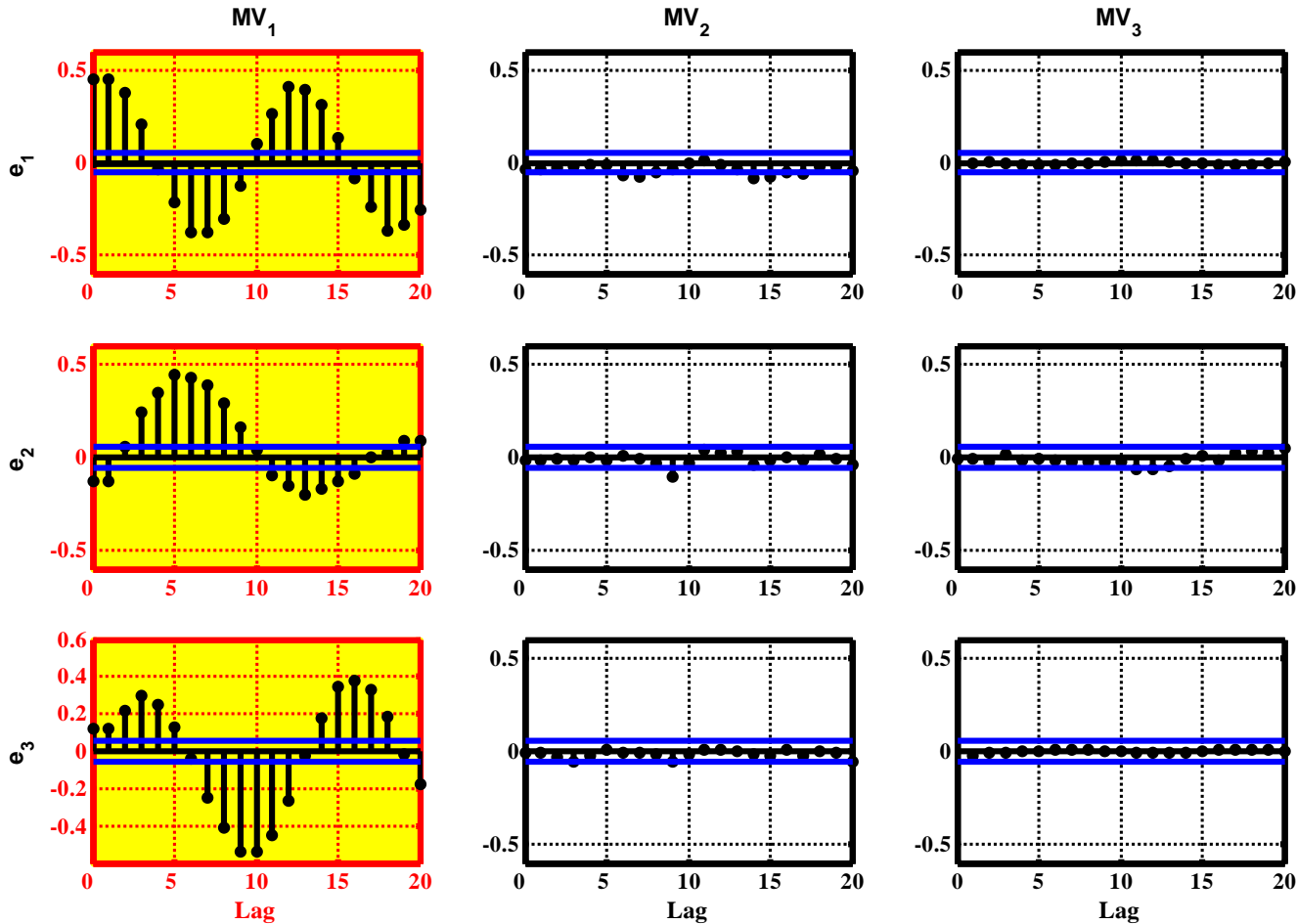
- Delay is underestimated by 2

Partial correlation coefficients between residuals and inputs

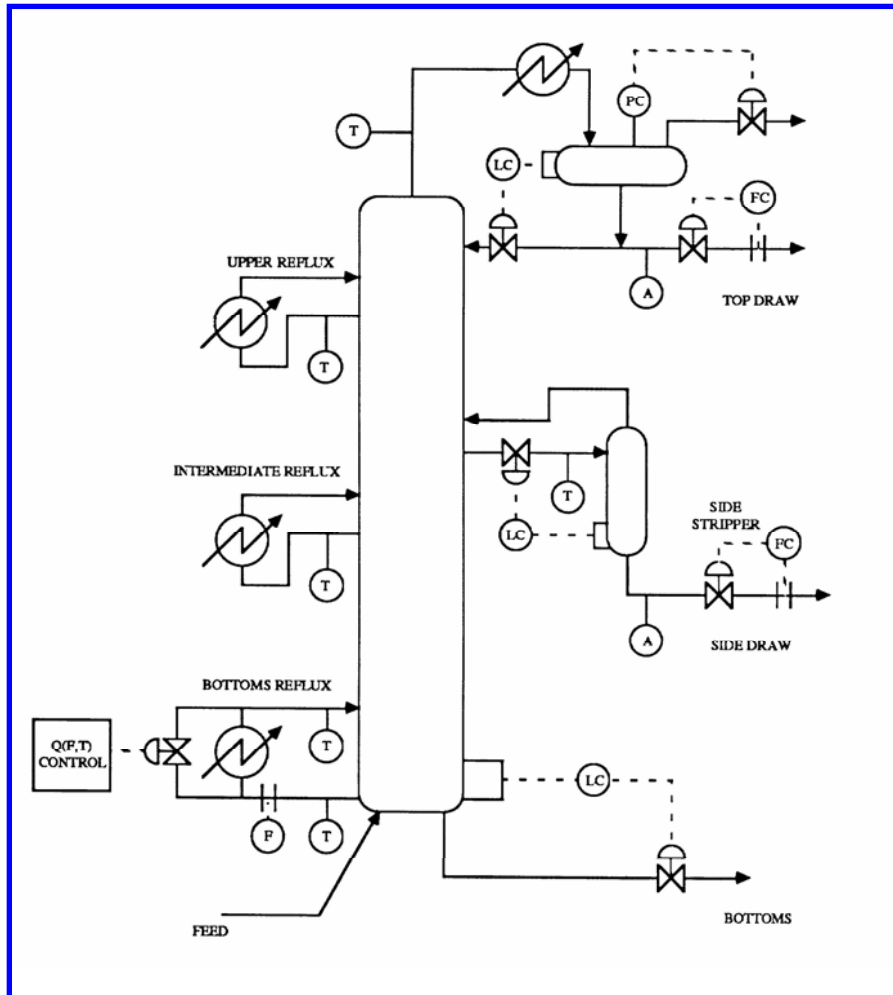
	MV1	MV2	MV3
e_1	0.45 (0)	-0.001 (0.45)	7.5e-4 (0.64)
e_2	-0.2(0)	-2e-4(0.43)	-2e-4(0.52)
e_3	0.18 (0)	-1.3e-4(0.61)	-1.4e-3(0.39)

**Mismatch correctly
located in channels
 u_1 - y_1, y_2, y_3**

Case Study 1 – Delay mismatch in u_1, y_1, y_2, y_3



Example: Shell Control Problem



Controlled Outputs :

- (y_1) Top End Point
- (y_2) Side Endpoint
- (y_3) Bottom Reflux Temp.

Manipulated Inputs :

- (u_1) Top Draw
- (u_2) Side Draw
- (u_3) Bottom Reflux Duty

Unmeasured Disturbances:

- (d_1) Upper reflux
- (d_2) Intermediate reflux

Process Dynamics

$$y(s) = G_u(s)u(s) + G_d(s)d(s)$$

$$G_u(s) = \begin{bmatrix} \frac{4.05e^{-27s}}{50s+1} & \frac{1.77e^{-28s}}{60s+1} & \frac{5.88e^{-27s}}{50s+1} \\ \frac{5.39e^{-18s}}{50s+1} & \frac{5.72e^{-14s}}{60s+1} & \frac{6.9e^{-15s}}{40s+1} \\ \frac{4.38e^{-20s}}{33s+1} & \frac{4.42e^{-22s}}{44s+1} & \frac{7.2e^{-19s}}{19s+1} \end{bmatrix}$$

- System with large time delays and significant multivariable interactions
- Time delay matrix is assumed to be known a-priori

Unmeasured Disturbance Dynamics

$$G_d(s) = \begin{bmatrix} \frac{1.2e^{-27s}}{45s+1} & \frac{1.44e^{-27s}}{40s+1} \\ \frac{1.52e^{-15s}}{25s+1} & \frac{1.83e^{-15s}}{20s+1} \\ 1.14 & 1.26 \\ \frac{1.14}{27s+1} & \frac{1.26}{32s+1} \end{bmatrix}$$

All disturbance inputs assumed to be piecewise constant

$$\begin{bmatrix} d_1(z) \\ d_2(z) \end{bmatrix} = \begin{bmatrix} z & \\ & z-0.95 \end{bmatrix} I \begin{bmatrix} w_1(z) \\ w_2(z) \end{bmatrix}$$

$$\text{mean}(w_i) = 0 ; \sigma(w_i) = 0.0075 \text{ for } i = 1,2$$

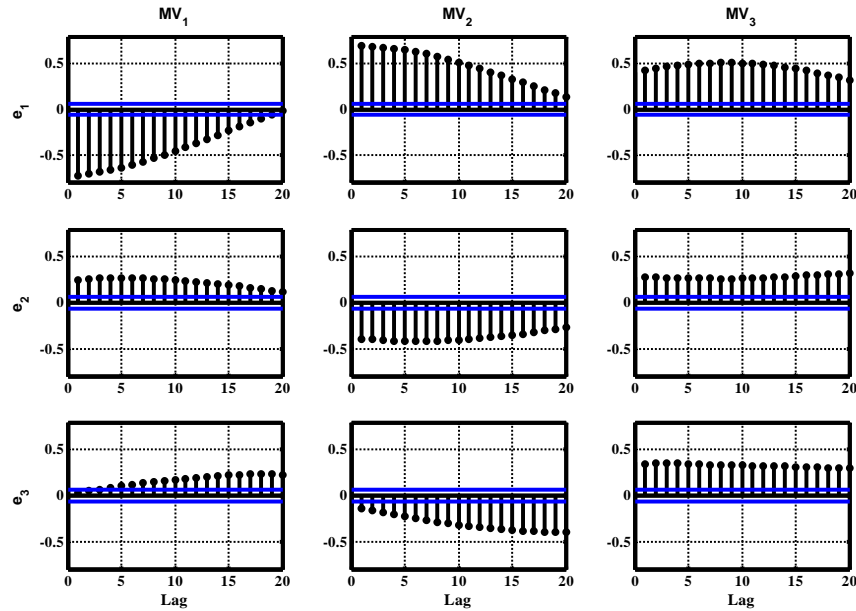
Measurement Noise

$$\text{mean}(v_i) = 0 ; \sigma(v_i) = 0.005 \text{ for } i = 1,2,3$$

Shell Control Problem – Scenario-1

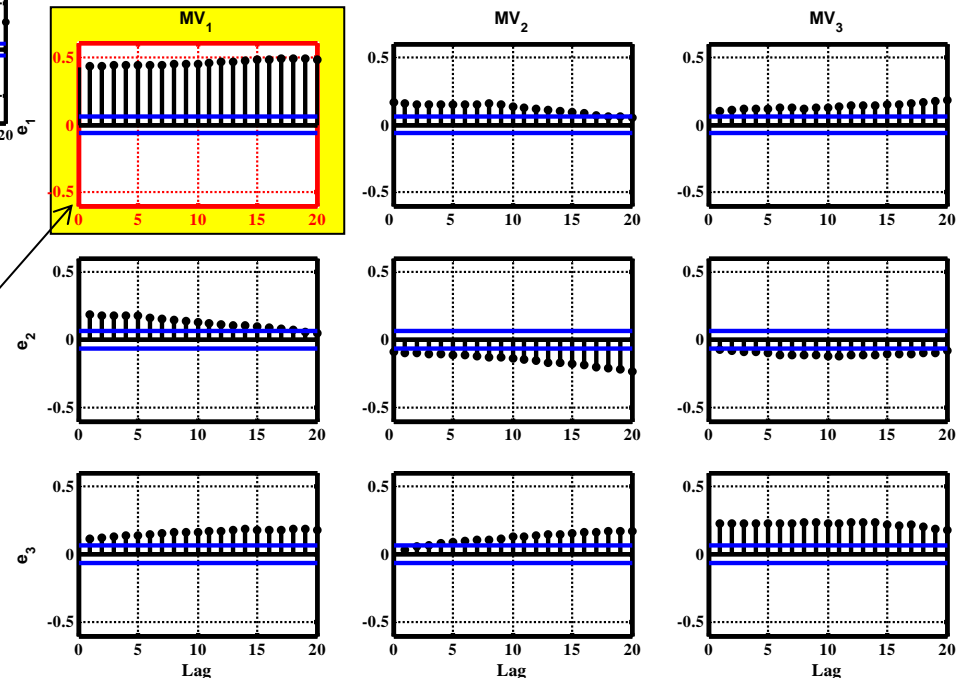
- 10 % gain mismatch and 10 % mismatch in time constant was added in all channels except channel u_1 - y_1 , where a larger mismatch of 50 % (underestimated gain) was added.
- Challenge is to identify the channel with significant mismatch.

Shell Control Problem: Scenario - 1



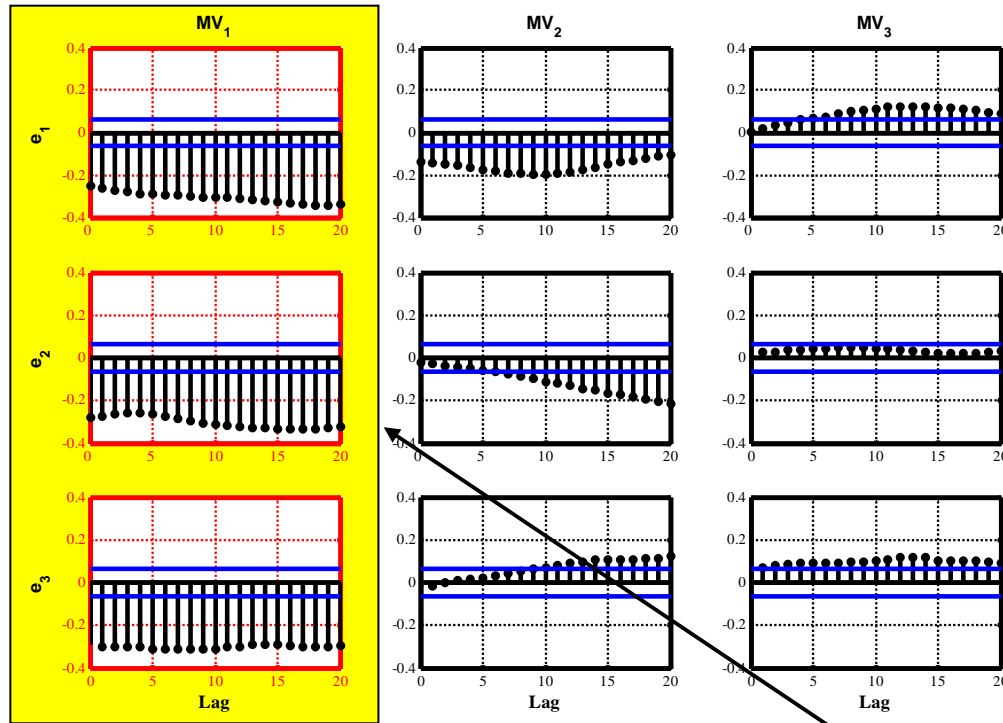
Regular correlation plots

Significant partial correlation between e_1 and u_1 implies significant mismatch in channel MV₁-CV₁



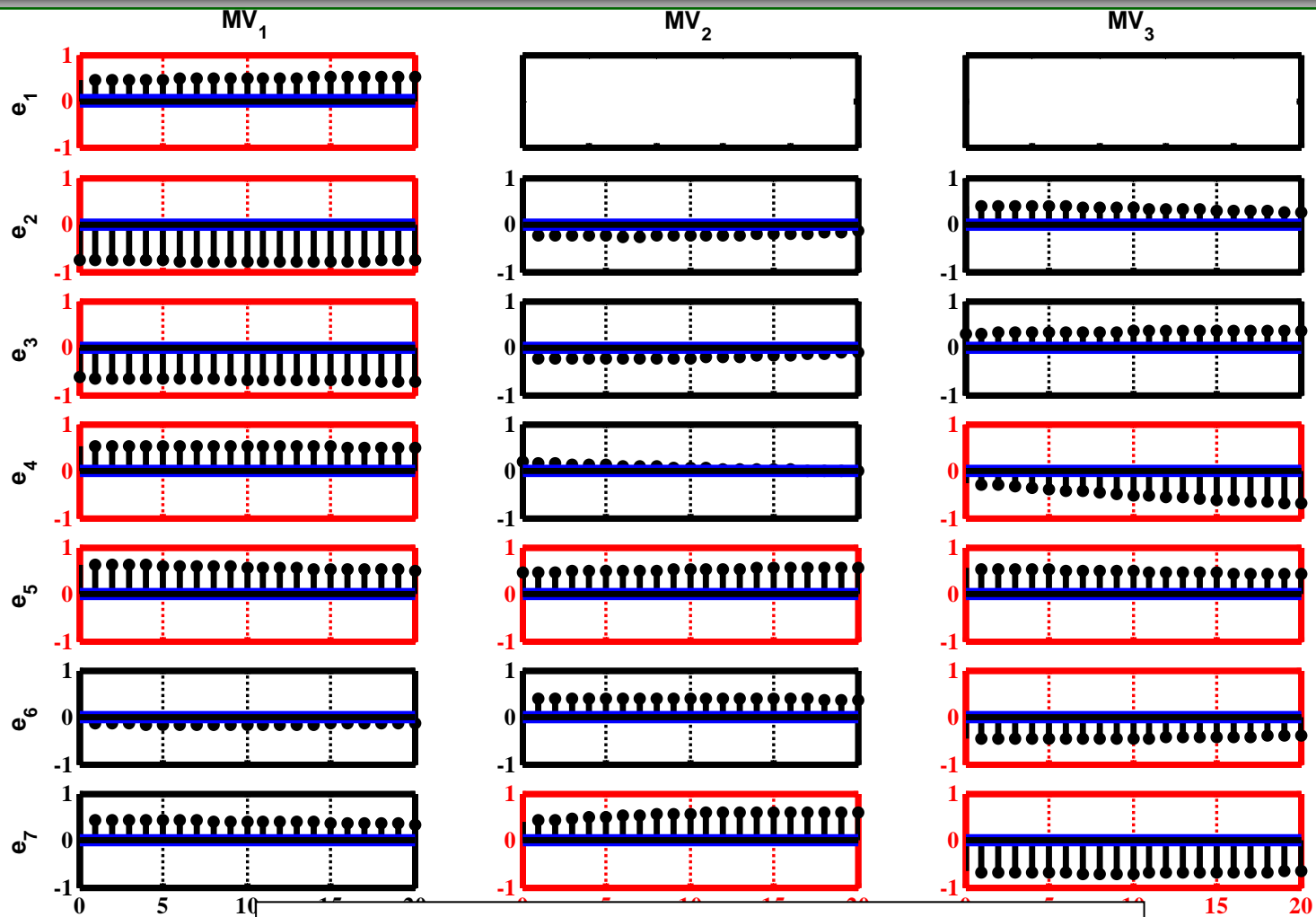
Shell Control Problem: Scenario - 2

- A mismatch in delay (underestimate) of 5 samples was introduced in MV1-CV1,CV2,CV3
- 10 % gain mismatch in all channels

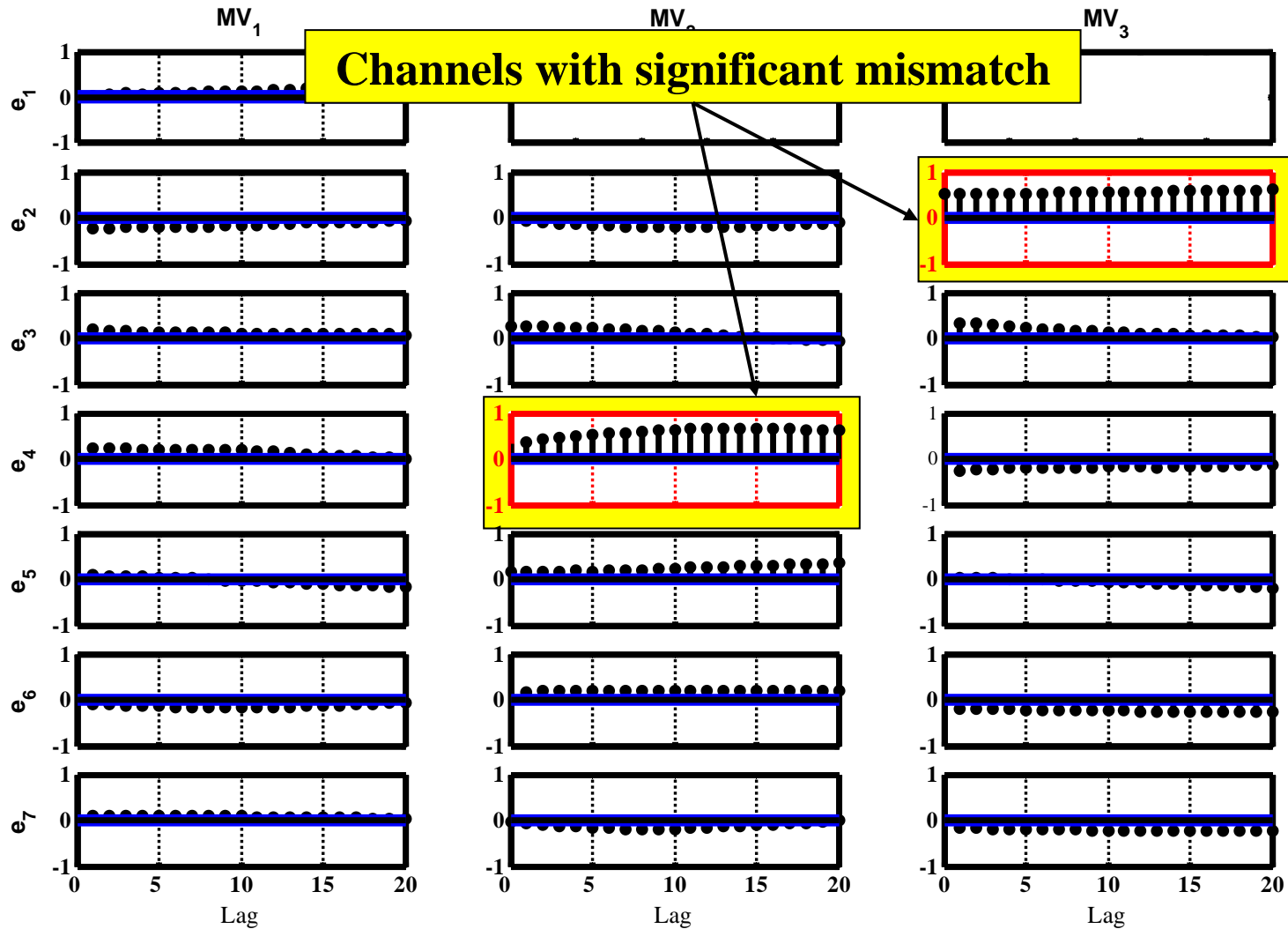


Significant partial correlations between e_1 , e_2 , e_3 and u_1 imply significant mismatches in channels MV_1 - CV_1 , CV_2 , CV_3

Industrial Case Study – KHU Unit at Suncor Energy⁴⁰



La **Regular correlation analysis does not help**



Concluding Remarks

1. Proposed a methodology for assessing the need for re-identification / re-tuning.
2. Demonstrated the efficacy on a SISO MPC simulation case study.
3. Proposed a technique based on partial correlations analysis for detection and isolation of mismatch.
4. Applied the technique successfully to simulated examples and industrial data.

Ongoing Work

- Assessing need for re-identification – Extension to the multivariable case
- Cancellation of effect of MPM – Re-tuning guidelines for MPC



Acknowledgements

1. Prof. Sirish Shah
2. Prof. Ravindra Gudi (IIT, Bombay)
3. Prof. Sachin Patwardhan (IIT, Bombay)
4. CPC Group Members
5. NSERC-Matrikon-Suncor-iCORE for financial support