

# Detection and Isolation of Model-Plant-Mismatch for Multivariate Dynamic Systems



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# Outline

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- Problem Formulation
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- Conclusion
- Acknowledgement

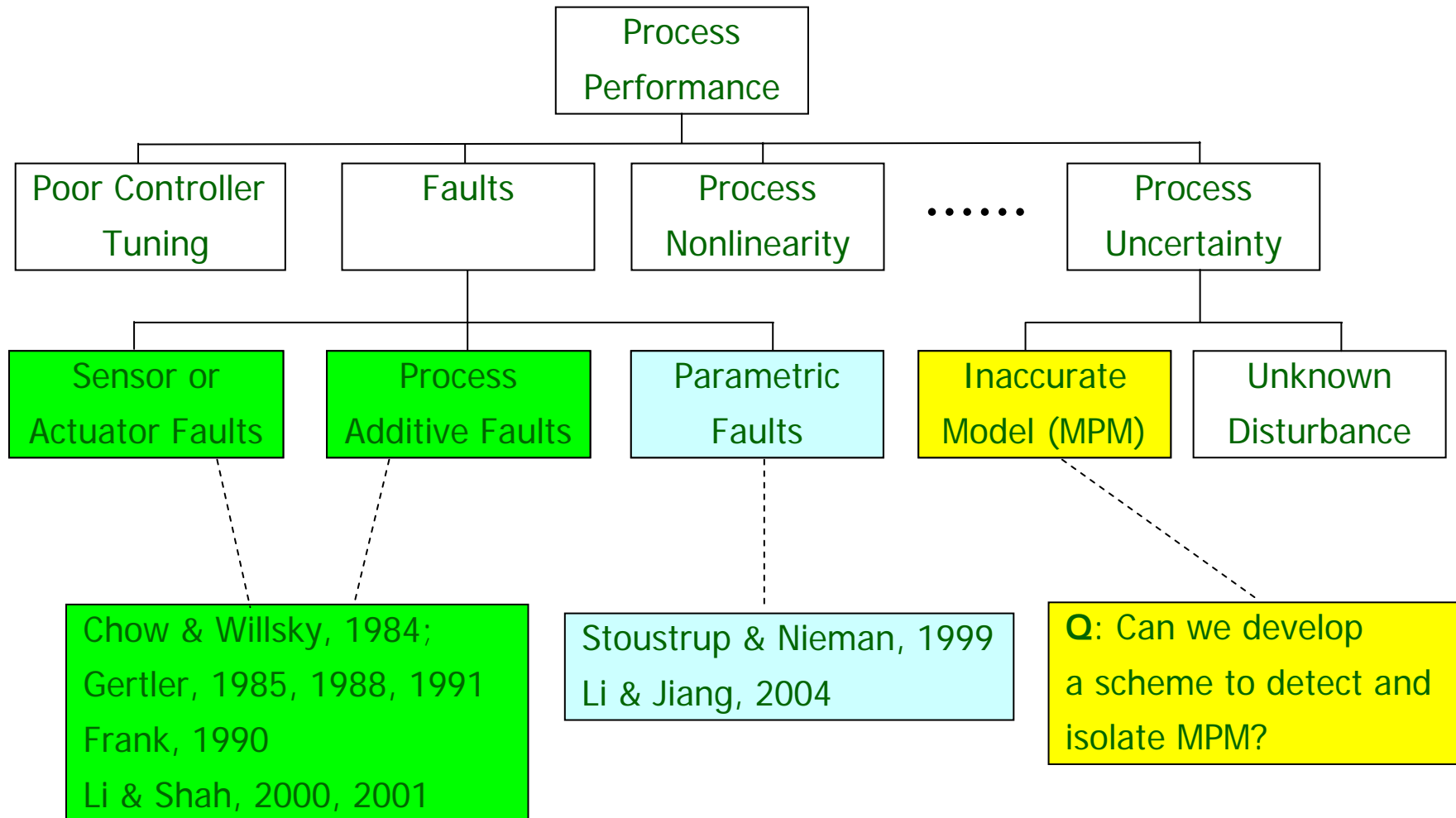
# Motivation & Literature Review

# Motivation

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- In industry, model-plant-mismatch (MPM) is a common and challenging problem for existing model-based control, e.g. MPC.
- In academia, MPM is still a difficult problem in the research area of fault detection and isolation (FDI).

# Literature Review on FDI



# Problem Formulation

# Problem Formulation

- Consider a LTI Discrete Time (DT) system:

$$\begin{cases} x(k+1) = \mathbf{A}_o x(k) + \mathbf{B}_o u(k) + p(k) \\ y(k) = \mathbf{C}_o x(k) + o(k) \end{cases}$$

- MPM effect:

Can we detect the mismatch?

Can we isolate the matrices that have mismatch?

$$\mathbf{A} = \mathbf{A}_o + \Delta\mathbf{A} \in R^{n \times n}$$

$$\mathbf{B} = \mathbf{B}_o + \Delta\mathbf{B} \in R^{n \times l}$$

$$\mathbf{C} = \mathbf{C}_o + \Delta\mathbf{C} \in R^{m \times n}$$

- A DT system with MPM:

$$\begin{cases} x(k+1) = (\mathbf{A}_o + \Delta\mathbf{A})x(k) + (\mathbf{B}_o + \Delta\mathbf{B})u(k) + p(k) \\ y(k) = (\mathbf{C}_o + \Delta\mathbf{C})x(k) + o(k) \end{cases}$$

# Problem Formulation (con't)

- Rewrite the MPM effect:

$$a(k) = \Delta \mathbf{A}x(k), \quad b(k) = \Delta \mathbf{B}u(k), \quad c(k) = \Delta \mathbf{C}x(k)$$

- Rewrite the system with MPM:

$$\begin{cases} x(k+1) = \mathbf{A}_0x(k) + \mathbf{B}_0u(k) + a(k) + b(k) + p(k) \\ y(k) = \mathbf{C}_0x(k) + c(k) + o(k) \end{cases}$$

$$a(k) \neq 0 \Rightarrow \Delta \mathbf{A} \neq 0$$

$$b(k) \neq 0 \Rightarrow \Delta \mathbf{B} \neq 0$$

$$c(k) \neq 0 \Rightarrow \Delta \mathbf{C} \neq 0$$

Can we indicate  $a(k), b(k)$  or  $c(k)$  are non-zero?



# MPM Detection and Isolation

# MPM Detection

- By stacking the equation for the system with MPM

$$y_s(k) - \mathbf{H}_s^o u_s(k) = \Gamma_s^o x(k-s) + c_s(k) + o_s(k) + \mathbf{G}_s^o [a_s(k) + b_s(k) + p_s(k)]$$

$$y_s(k) = \begin{bmatrix} y(k-s) \\ y(k-s+1) \\ \vdots \\ y(k) \end{bmatrix} \in R^{m_s} \quad \Gamma_s^o = \begin{bmatrix} \mathbf{C}_o \\ \mathbf{C}_o \mathbf{A}_o \\ \vdots \\ \mathbf{C}_o \mathbf{A}_o^s \end{bmatrix} \in R^{m_s \times n}$$

$m_s = m(s+1)$

$$\mathbf{H}_s^o = \begin{bmatrix} \mathbf{0} & \dots & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{C}_o \mathbf{B}_o & \mathbf{0} & \dots & \vdots & \vdots \\ \mathbf{C}_o \mathbf{A}_o \mathbf{B}_o & \mathbf{C}_o \mathbf{B}_o & \ddots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \mathbf{0} & \mathbf{0} \\ \mathbf{C}_o \mathbf{A}_o^{s-1} \mathbf{B}_o & \mathbf{C}_o \mathbf{A}_o^{s-2} \mathbf{B}_o & \dots & \mathbf{C}_o \mathbf{B}_o & \mathbf{0} \end{bmatrix} \quad \mathbf{G}_s^o = \begin{bmatrix} \mathbf{0} & \dots & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{C}_o & \mathbf{0} & \dots & \vdots & \vdots \\ \mathbf{C}_o \mathbf{A}_o & \mathbf{C}_o & \ddots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \mathbf{0} & \mathbf{0} \\ \mathbf{C}_o \mathbf{A}_o^{s-1} & \mathbf{C}_o \mathbf{A}_o^{s-2} & \dots & \mathbf{C}_o & \mathbf{0} \end{bmatrix}$$

# MPM Detection (con't)

- By stacking the equation for the system with MPM

$$y_s(k) - \mathbf{H}_s^o u_s(k) = \cancel{\Gamma_s^o x(k-s)} + c_s(k) + o_s(k) + \mathbf{G}_s^o [a_s(k) + b_s(k) + p_s(k)]$$

$$\mathbf{W}_o \Gamma_s^o = 0$$

$$\Gamma_s^o \in R^{m_s \times n} \Rightarrow \mathbf{W}_o \in R^{(m_s - n) \times m_s}$$

$$e_s(k) \equiv \mathbf{W}_o [y_s(k) - \mathbf{H}_s^o u_s(k)]$$

Primary residual vector (PRV)

$$= \underbrace{\mathbf{W}_o [o_s(k) + \mathbf{G}_s^o p_s(k)]}_{e_s^*(k)} + \underbrace{\mathbf{W}_o \{c_s(k) + \mathbf{G}_s^o [a_s(k) + b_s(k)]\}}_{e_s^f(k)}$$

Zero-mean, Gaussian distributed random noise vector

Non-zero vector, if there is MPM

# PRV Properties

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- If we assume the covariance of  $p(k)$  &  $o(k)$  as

$$\mathbf{R}_p \in R^{n \times n}, \quad \mathbf{R}_o \in R^{m \times m}$$

- Then the covariance of  $p_s(k)$  &  $o_s(k)$  is:

$$\mathbf{R}_{s,p} = \mathbf{I}_{s+1} \otimes \mathbf{R}_p \in R^{n_s \times n_s}$$

$$\mathbf{R}_{s,o} = \mathbf{I}_{s+1} \otimes \mathbf{R}_o \in R^{m_s \times m_s}$$

- Then the covariance of  $e_s^*(k) = \mathbf{W}_o[o_s(k) + \mathbf{G}_s^o p_s(k)]$  is:

$$\mathbf{R}_{s,e} = \mathbf{W}_o(\mathbf{G}_s^o \mathbf{R}_{s,p} \mathbf{G}_s^{oT} + \mathbf{R}_{s,o}) \mathbf{W}_o^T$$

$$\in R^{(m_s-n) \times (m_s-n)}$$

# PRV Properties (con't)

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- The PRV follows multivariate Gaussian distribution

No MPM  $\mathbf{e}_s(k) = \mathbf{e}_s^*(k) \sim \mathcal{N}(0, \mathbf{R}_{s,e})$

MPM  $\mathbf{e}_s(k) = \mathbf{e}_s^*(k) + \mathbf{e}_s^f(k) \sim \mathcal{N}(\mathbf{e}_s^f(k), \mathbf{R}_{s,e})$

- The PRV can be further transformed into a square weighted residual which is sensitive to the mismatch in  $\{\mathbf{A}, \mathbf{B}, \mathbf{C}\}$  .

$$\eta_{ABC}(k) = (e_s(k))^T \times \mathbf{R}_{s,e}^{-1} \times e_s(k)$$

# MPM Detection Index (1)

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- It follows chi-square distribution if there is no MPM:

$$\eta_{ABC}(k) \sim \chi_{m_s-n}^2(\alpha)$$

- Given a confidence limit, e.g.  $\alpha = 1\%$  .

$$\eta_{ABC}(k) > \chi_{m_s-n}^2(\alpha) \Rightarrow$$

This is mismatch in **A**  
or **B** or **C** .

$$\eta_{ABC}(k) < \chi_{m_s-n}^2(\alpha) \Rightarrow$$

This is no mismatch in **A**,  
**B** and **C** .

# MPM Detection Indices (2) & (3)

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- Other two MDIs are proposed in the similar way:
  - $\eta_{AC}(k)$  is only sensitive to the mismatch in  $\{\mathbf{A}, \mathbf{C}\}$  ;
  - $\eta_C(k)$  is only sensitive to the mismatch in  $\{\mathbf{C}\}$  .

# Isolation Logic

$\eta_{ABC}(k)$	$\eta_{AC}(k)$	$\eta_C(k)$	Fault Matrix
1	0	0	<b>B</b>
1	1	0	<b>A</b> or <b>AB</b>
1	1	1	<b>C</b> or <b>AC</b> or <b>BC</b> or <b>ABC</b>

'1': the according MDI does indicate MPM

'0': the according MDI doesn't indicate MPM



# Isolation Logic (con't)

- Usually, matrix **C** is the sensor gain matrix, which is unlikely to deviate.
- Therefore, if we assume there is no mismatch in matrix **C**, the isolation logic becomes:

$\eta_{ABC}(k)$	$\eta_{AC}(k)$	Fault Matrix
1	0	<b>B</b>
1	1	<b>A</b> or <b>AB</b>

'1': the according MDI does indicate MPM

'0': the according MDI doesn't indicate MPM

# Numerical Example

# The simulated process

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- The simulated process is a second order dynamic system.
- The system matrices in discrete time domain are:

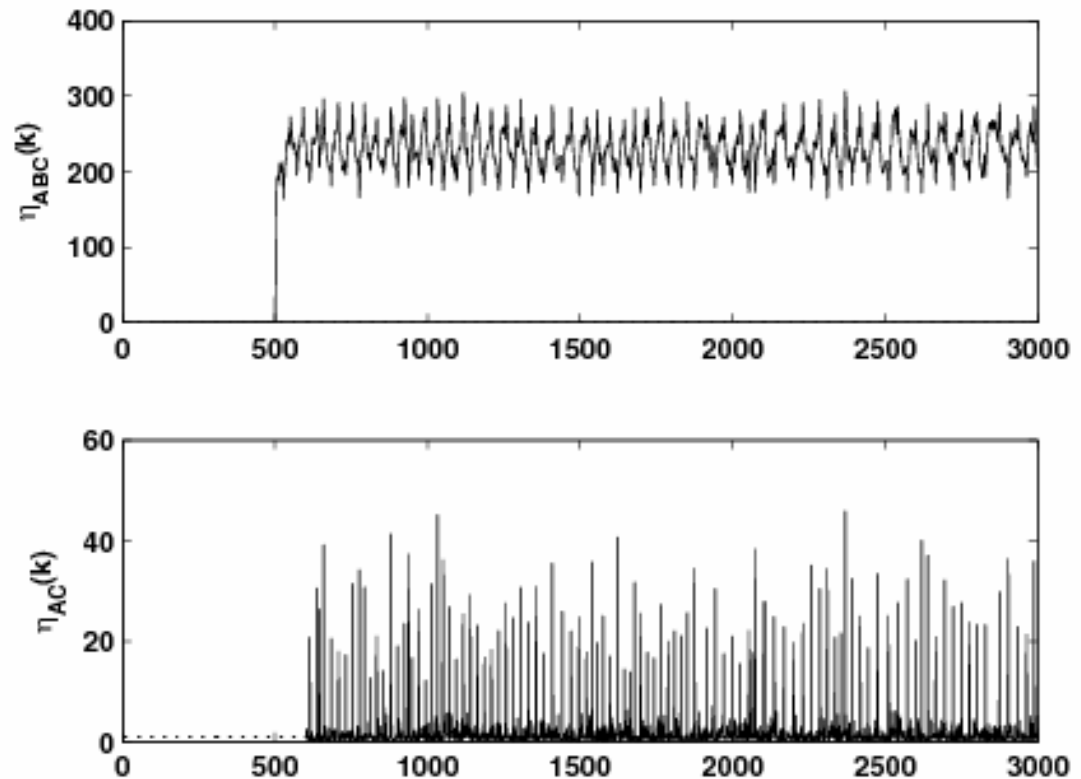
$$\mathbf{A}_0 = \begin{bmatrix} 0.6082 & -0.0100 \\ 2.2668 & 0.0364 \end{bmatrix} \quad \mathbf{B}_0 = \begin{bmatrix} 0.5602 & 0.0008 \\ 1.3760 & 0.3026 \end{bmatrix}$$

$$\mathbf{C}_0 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

- Matrix **C** is the sensor gain matrix and we assume there is no mismatch in this matrix.

# Case(1): mismatch in **A** matrix

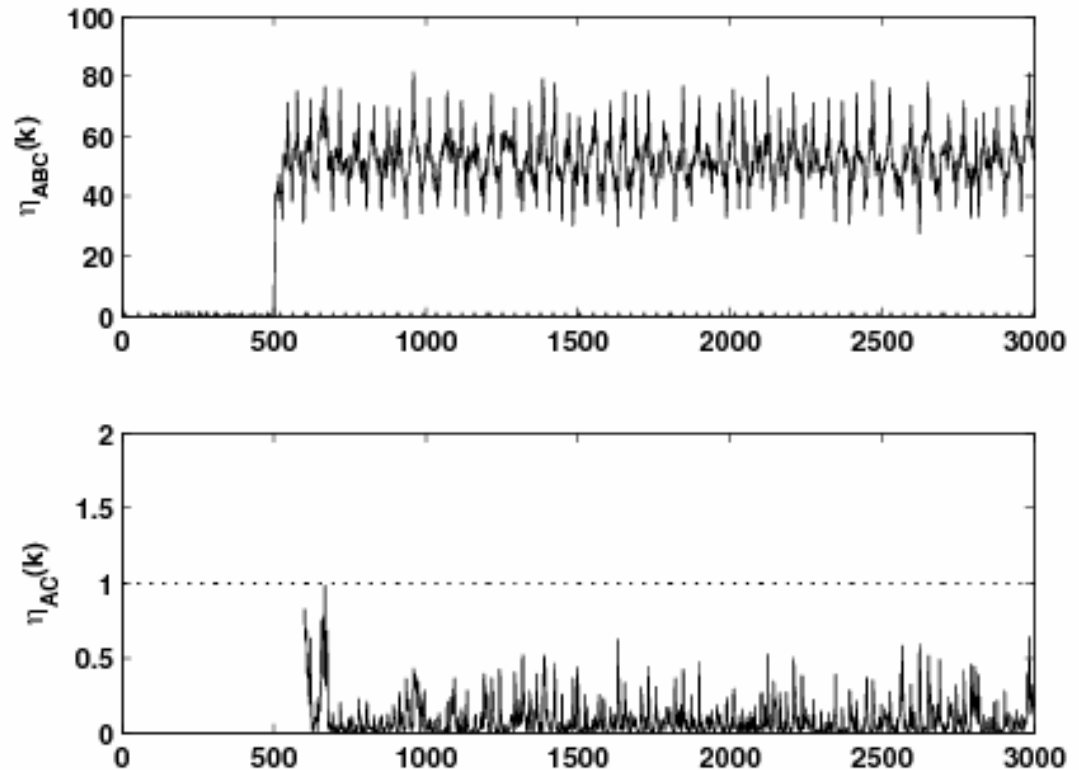
- 10% mismatch in **A** matrix;
- 3000 samples of input and output data;
- Mismatch is introduced at 500<sup>th</sup> sample;
- Noise-to-signal ration (NSR) for the two outputs are 11.19% and 2.73%.



- Remark: The MDIs have confirmed that there is mismatch in matrix **A**.

# Case(2): mismatch in **B** matrix

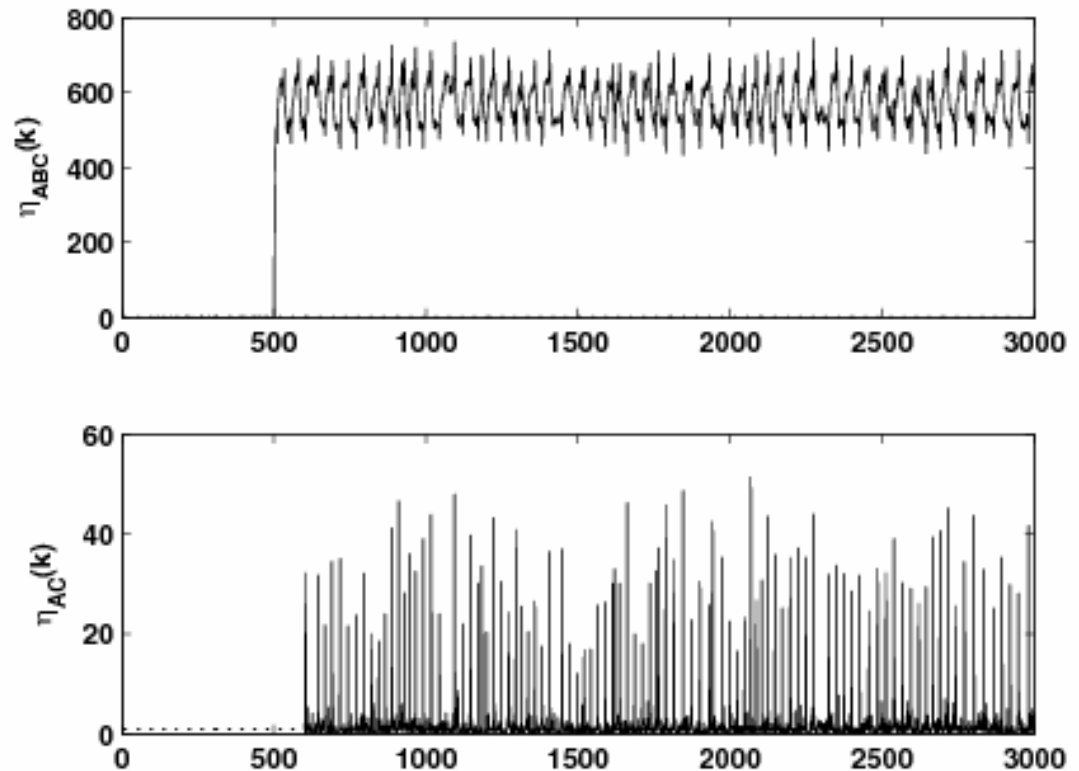
- 10% mismatch in **B** matrix;
- 3000 samples of input and output data;
- Mismatch is introduced at 500<sup>th</sup> sample;
- Noise-to-signal ration (NSR) for the two outputs are 14.81% and 4.12%.



- Remark: The MDIs have confirmed that the mismatch is only in matrix **B**.

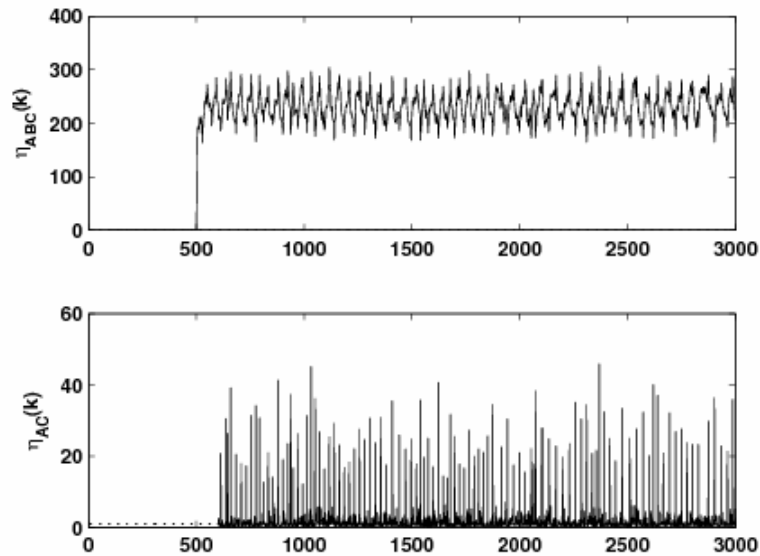
# Case(3): mismatch in **A** & **B** matrices

- 10% mismatch in **A** & **B** matrices;
- 3000 samples of input and output data;
- Mismatch is introduced at 500<sup>th</sup> sample;
- Noise-to-signal ration (NSR) for the two outputs are 6.94% and 1.74%.

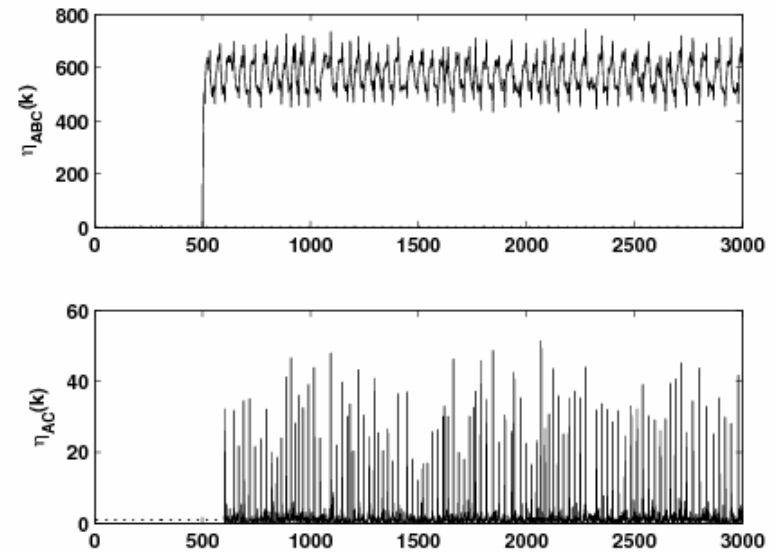


- Remark: The MDIs have confirmed that there is mismatch in matrix **A**.

# Comparison of case (1) & case (3)



➤ Case (1): 10% mismatch in **A**



➤ Case (3): 10% mismatch in **A & B**

- $\eta_{ABC}(k)$  is sensitive to both mismatch in **A & B**
- $\eta_{AC}(k)$  is only sensitive to mismatch in **A**

# Conclusion



# Conclusion

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- The types of faults that can affect process performance haven been reviewed.
- Three different MDIs have been proposed to detect MPM.
- An isolation logic framework has been proposed to isolate the system matrices that have MPM.
- A numerical example has been presented to demonstrate the efficacy of the new scheme for detection and isolation of MPM.

# Acknowledgement

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