Cautious Data Driven Fault Detection and Isolation applied to the Wind Turbine Benchmark

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“Standard” WT Modeling Approach

Windturbine Modeling Package

Geometrical, Material cst, Atmospheric Data, ...

"Dynamic" Mathematical Model
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Windturbine Modeling Package

Geometrical, Material cst, Atmospheric Data, ...

"Dynamic" Mathematical Model

Features

- Multi-physics modeling environments (Aero-, Mech-, Ele-, Pneu-, Hydro, Marit-, Embed-, etc.)
**“Standard” WT Modeling Approach**

**Windturbine Modeling Package**

- Geometrical, Material cst, Atmospheric Data, ...
- "Dynamic" Mathematical Model

**Features**

- Multi-physics modeling environments (Aero-, Mech-, Ele-, Pneu-, Hydro, Marit-, Embed-, etc.) → *Complexity*
- Major (proprietary) data bases of “validated” subcomponents
- .... And control design features.

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Getting real-life ...

Alternative Feedback Control Design Methods

- “Glueing” together single loop feedback controllers designed for linearized $FP^a$ models
Alternative Feedback Control Design Methods

- “Glueing” together single loop feedback controllers designed for linearized FP \(^a\) models → time consuming
- Robust Multivariable control based on linearized FP models (making use of “Coleman transform”)

\(^a\)First Principles
### Alternative Feedback Control Design Methods

- “Glueing” together single loop feedback controllers designed for linearized FP models → time consuming
- Robust Multivariable control based on linearized FP models (making use of “Coleman transform”)

---

### Standing questions

- Commissioning still needs to be done!
- How to get the model uncertainty?
- How to get realistic disturbance models?
- How to (re-)configure the controller?
Getting real-life ...

### Alternative Feedback Control Design Methods

- “Glueing” together single loop feedback controllers designed for linearized FP\(^a\) models → time consuming
- Robust Multivariable control based on linearized FP models (making use of “Coleman transform”)

\(^a\)First Principles

### Standing questions

- Commissioning still needs to be done!
- How to get the model uncertainty?
- How to get realistic disturbance models?
- How to (re-)configure the controller? Cautious Data Driven FDI as a starting point!
The “Classical” Data Driven design cycle

\[
\begin{align*}
x(k + 1) & = Ax(k) + Bu(k) + Ke(k) \\
y(k) & = Cx(k) + Du(k) + e(k)
\end{align*}
\]
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Problems with the Classical Data Driven Design Cycle

due to fault? or model uncertainty?
Streamlining Data Driven Synthesis

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- Results on the WT benchmark
Fault Detection using Identified model?

\[ e(k) \]
\[ u(k) \rightarrow d \rightarrow y(k) \]

\[ \hat{r}(k) = y(k) - \hat{d} \cdot u(k) \]
\[ \hat{d} = \mathcal{Y}_{t,1,N} \cdot \mathcal{U}_{t,1,N}^\dagger \]
Fault Detection using Identified model?

\[ u(k) \rightarrow d \rightarrow y(k) \]

\[ e(k) \]

\[ r(k) = y(k) - \hat{d} \cdot u(k) \]

\[ \hat{d} = \mathcal{V}_{t,1,N} \cdot \mathcal{U}_{t,1,N}^{\dagger} \]

Distribution of \( \Delta \hat{d} \)

\[ \Delta \hat{d} = d - \hat{d} = \mathcal{E}_{t,1,N} \cdot \mathcal{U}_{t,1,N}^{\dagger} \]

\[ \text{var}(\Delta \hat{d}) = \frac{\sigma^2_e}{\mathcal{U}_{t,1,N} \mathcal{U}^T_{t,1,N} / N} \]
Why & What is Cautious Fault Detection?

\[
\text{var}(\hat{r}(k)) = \text{var}(\Delta \hat{d} \cdot u(k)) + \text{var}(e(k))
\]

\[
= u^2(k) \cdot \text{var}(\Delta \hat{d}) + \sigma_e^2 = \left\{ \frac{u^2(k) \cdot \sigma_e^2}{Ut_{t,1,N}U^T_{t,1,N}/N} \right\} + \sigma_e^2
\]
Why & What is Cautious Fault Detection?

\[ \text{var}(\hat{r}(k)) = \text{var}(\Delta \hat{d} \cdot u(k)) + \text{var}(e(k)) \]
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Data Driven Fault Detection for LTI SSM

\[ \Sigma : \begin{align*}
    x(k + 1) &= Ax(k) + Bu(k) + Ke(k) \\
    y(k) &= Cx(k) + Du(k) + e(k)
\end{align*} \]
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Data Driven Fault Detection Identification Problem

Given i/o data sequences \( \{u(k), y(k)\}_{k=1}^N \) from the “nominal” (fault-free) system, determine a fault detection filter:

\[
r(k) = F \left( u(k), y(k) \right)
\]

and its test statistic.
Data equation for SI

Consider $\Sigma$ represented in innovation form:

\[
\begin{align*}
\dot{x}(k+1) &= (A - KC) \hat{x}(k) + (B - KD) u(k) + K y(k) \\
y(k) &= C \hat{x}(k) + Du(k) + e(k)
\end{align*}
\]

with the innovation signal $e(k)$ zero-mean white noise with covariance matrix $R_e$. 
Data equation for SI

Consider $\Sigma$ represented in innovation form:

\[
\begin{align*}
\hat{x}(k+1) &= (A - KC) \hat{x}(k) + (B - KD) u(k) + Ky(k) \\
y(k) &= C\hat{x}(k) + Du(k) + e(k)
\end{align*}
\]

with the innovation signal $e(k)$ zero-mean white noise with covariance matrix $R^e$.

Further, let $z(t)^T = [u(t)^T \quad y(t)^T]$, then we can write the state $\hat{x}(t)$ as:

\[
\hat{x}(t) = \Phi^p \hat{x}(t-p) + \Phi^{p-1}[\tilde{B}, K] \quad \Phi^{p-2}[\tilde{B}, K] \quad \cdots \quad [\tilde{B}, K]
\]

where $L_p = \begin{bmatrix} z(t-p) \\ z(t-p+1) \\ \vdots \\ z(t-1) \end{bmatrix}$.
Data equation for PBSID (Chiuso 2007)

\[ \mathcal{Y}_{t,L,1} = [I_L \otimes (C\Phi^p)] \cdot \hat{x}(t - p) + \]

\[ \begin{bmatrix}
  C\Phi^p^{-1}[\tilde{B}, K] & C\Phi^p^{-2}[\tilde{B}, K] & \cdots & C[\tilde{B}, K] \\
  0 & C\Phi^p^{-1}[\tilde{B}, K] & \cdots & C\Phi[\tilde{B}, K] \\
  \vdots & \vdots & \ddots & \vdots \\
  0 & 0 & \cdots & C\Phi^L-1[\tilde{B}, K]
\end{bmatrix} \cdot \mathcal{Z}_{t-p,p,1} + \]

\[ \mathcal{H}_z^L = \begin{bmatrix}
  [D, 0] \\
  C[\tilde{B}, K] \\
  \vdots \\
  C\Phi^L-2[\tilde{B}, K] & C\Phi^L-3[\tilde{B}, K] & \cdots & [D, 0]
\end{bmatrix}
\]

\[ \mathcal{Z}_{t,L,1} + \mathcal{E}_{t,L,1} \]
Data equation for PBSID (Chiuso 2007)

Assuming $\Phi^p \approx 0$:

\[ Y_{t,L,N} \approx \begin{bmatrix} C\Phi^{p-1}[\tilde{B}, K] & C\Phi^{p-2}[\tilde{B}, K] & \cdots & C[\tilde{B}, K] \\ C\Phi^p[\tilde{B}, K] & C\Phi^{p-1}[\tilde{B}, K] & \cdots & C\Phi[\tilde{B}, K] \\ \vdots & \vdots & \ddots & \vdots \\ C\Phi^{p-1+L}[\tilde{B}, K] & \cdots & \cdots & C\Phi^{L-1}[\tilde{B}, K] \end{bmatrix} \cdot \mathcal{Z}_{t-p,p,N} = \mathcal{O}_L \mathcal{L}_p \approx \mathcal{H}_z^{L,p} \]

\[ \mathcal{Z}_{t,L,N} + \mathcal{E}_{t,L,N} \]

\[ \begin{bmatrix} [D, 0] \\ C[\tilde{B}, K] \\ \vdots \\ C\Phi^{L-2}[\tilde{B}, K] & C\Phi^{L-3}[\tilde{B}, K] & \cdots & [D, 0] \end{bmatrix} \]
Parameter identification errors in closed-loop identification

Biased LS estimates

Denote $\Xi = \begin{bmatrix} C \Phi^{p-1} [ \tilde{B} & K ] & \cdots & C [ \tilde{B} & K ] & D \end{bmatrix}$.

$$\hat{\Xi} = Y_{t,1,N} \cdot \begin{bmatrix} Z_{t-p,p,N} \\ U_{t,1,N} \end{bmatrix} \dagger$$

$$\hat{\Sigma}_e = Cov \left( Y_{t,1,N} - \hat{\Xi} \cdot Z_i \right)$$
Parameter identification errors in closed-loop identification

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Biased LS estimates
Denote $\Xi = \begin{bmatrix} C \Phi^{-1} & [\tilde{B} & K] & \cdots & C & [\tilde{B} & K] & D \end{bmatrix}$.

$$\hat{\Xi} = \mathcal{V}_{t,1,N} \cdot \begin{bmatrix} \mathcal{Z}_{t-p,p,N} \\ \mathcal{U}_{t,1,N} \end{bmatrix}^{\dagger}$$

$$\hat{\Sigma}_{e} = \text{Cov} \left( \mathcal{V}_{t,1,N} - \hat{\Xi} \cdot \mathcal{Z}_{i} \right)$$

$\text{vec}(\hat{\Xi}) \triangleq \hat{\Theta}$ contains the following errors.

$$\hat{\Theta} - \Theta = \delta \Theta + \Sigma_{\hat{\Theta}}^{1/2} \cdot \epsilon \quad \epsilon \sim (0, I)$$

$$\Sigma_{\hat{\Theta}} = \left( \mathcal{Z}_{i} \mathcal{Z}_{i}^{T} \right)^{-1} \otimes \hat{\Sigma}_{e}$$
Recall the data equation:

\[ Y_{t,L,N} = [I_L \otimes (C\Phi^p)] \cdot X_{t-p,L,N} + H_{zL,p} \cdot Z_{t-p,p,N} + T_{zL} Z_{t,L,N} + E_{t,L,N} \]

Work with an (accurate) approximation:

\[ O_L \cdot \mathcal{X}_{t,1,N} \approx H_{zL,p} \cdot Z_{t-p,p,N} \]

\[ O_L \cdot \mathcal{X}_{t,1,N} \approx \partial \text{LS estimates} \cdot Z_{t-p,p,N} \]

\[ O_L \cdot \mathcal{X}_{t,1,N} \approx \partial \text{past I/Os} \]
Recall the data equation:

\[
\mathcal{Y}_{t,L,N} = [I_L \otimes (C\Phi^p)] \cdot \mathcal{X}_{t-p,L,N} + \underbrace{\mathcal{H}^{L,p}_z \cdot \mathcal{Z}_{t-p,p,N}}_{\text{LS estimates}} + \underbrace{T^L_z \mathcal{Z}_{t,L,N} + \mathcal{E}_{t,L,N}}_{\text{past I/Os}}
\]

Get an estimate of the left null space of \( \mathcal{O}_L \):

\[
\mathcal{O}_L \cdot \mathcal{X}_{t,1,N} \approx \underbrace{\mathcal{H}^{L,p}_z \cdot \mathcal{Z}_{t-p,p,N}}_{\text{LS estimates}} \text{ past I/Os}
\]

\[
\mathcal{H}^{L,p}_z \cdot \mathcal{Z}_{t-p,p,N} = \left[ \begin{array}{c} U_{\mathcal{H}Z} \\ \left( U^\perp_{\mathcal{H}Z} \right)^T \end{array} \right] \cdot \left[ \begin{array}{cc} S_{\mathcal{H}Z} & 0 \\ 0 & S^\perp_{\mathcal{H}Z} \end{array} \right] \cdot \left[ \begin{array}{c} V^T_{\mathcal{H}Z} \\ \left( V^\perp_{\mathcal{H}Z} \right)^T \end{array} \right].
\]
Recall the data equation:

\[ \mathbf{y}_{t,L,N} = [I_L \otimes (C\Phi^p)] \cdot \mathbf{x}_{t-p,L,N} + \mathbf{H}_{z}^{L,p} \cdot \mathbf{z}_{t-p,p,N} + \mathbf{T}_{z}^{L} \cdot \mathbf{z}_{t,L,N} + \mathbf{e}_{t,L,N} \]

Define the residual and its statistic?

\[ \mathbf{O}_{L} \cdot \mathbf{x}_{t,1,N} \approx \mathbf{H}_{z}^{L,p} \cdot \mathbf{z}_{t-p,p,N} = \left[ U_{HZ} \ U_{HZ}^{\perp} \right] \cdot \left[ S_{HZ} \ 0 \right] \cdot \left[ V_{HZ}^{T} \left( V_{HZ}^{\perp} \right)^{T} \right] \cdot \left( I - \mathbf{T}_{y}^{L} \right) \cdot \mathbf{y}_{k,L} - \mathbf{T}_{u}^{L} \cdot \mathbf{u}_{k,L} \]

Identifying a parity relation from data (DD-PSA)
Disadvantages DD-PSA

Approximation in the SVD AND annihilate what is known!

\[ \mathcal{H}_z^{L,p} \cdot Z_{t-p,p,N} = \begin{bmatrix} U_{HZ} & U_{HZ}^\perp \end{bmatrix} \cdot \begin{bmatrix} S_{HZ} & 0 \\ 0 & S_{HZ}^\perp \end{bmatrix} \cdot \begin{bmatrix} V_{HZ}^T \\ (V_{HZ}^\perp)^T \end{bmatrix}. \]

\[ (U_{HZ}^\perp)^T \cdot O_L \neq 0. \]
Disadvantages DD-PSA

Approximation in the SVD AND annihilate what is known!

\[
\mathcal{H}_Z^{L,p} \cdot Z_{t-p,p,N} = [U_{HZ} \quad U_{HZ}^\perp] \cdot \begin{bmatrix}
S_{HZ} & 0 \\
0 & S_{HZ}^\perp
\end{bmatrix} \cdot \begin{bmatrix}
V_{HZ}^T \\
(V_{HZ}^\perp)^T
\end{bmatrix}.
\]

\[
(U_{HZ}^\perp)^T \cdot O_L \neq 0.
\]

Uncertainty in the residual generator

\[
r_{psa}^{k,L} = \left( U_{HZ}^\perp \right)^T \begin{pmatrix}
(I - \mathcal{T}_y^L) \\
\mathcal{U}_y^L
\end{pmatrix} y_{k,L} - \begin{pmatrix}
\mathcal{U}_u^L
\end{pmatrix} u_{k,L}.
\]

Nonlinear dependence of the stochastic uncertainties in \( r_{psa}^{k,L} \) on the parametric errors in \( \mathcal{H}_Z^{L,p}, \mathcal{T}_y^L, \mathcal{T}_u^L \).
Recall the data equation:

\[
Y_{t,L,N} = [I_L \otimes (C \Phi^p)] \cdot X_{t-p,L,N} + H_{z}^{L,p} \cdot Z_{t-p,p,N} + T_{z}^{L} Z_{t,L,N} + E_{t,L,N}
\]

LS estimates

past I/Os
Identifying a parity relation from data (FICSI) - nominal

Recall the data equation:

\[ Y_{t,L,N} = [I_L \otimes (C \Phi^p)] \cdot X_{t-p,L,N} + H_{z,p} \cdot Z_{t-p,p,N} + T_L Z_{t,L,N} + \mathcal{E}_{t,L,N} \]

Work directly! with an (accurate) approximation:

\[ Y_{t,L,N} \approx H_{z,p} \cdot Z_{t-p,p,N} + T_L Z_{t,L,N} + \mathcal{E}_{t,L,N} \]
Identifying a parity relation from data (FICSI) - nominal

Recall the data equation:

\[ \mathcal{Y}_{t,L,N} = [I_L \otimes (C\Phi^p)] \cdot \mathcal{X}_{t-p,L,N} + H^L_p \cdot \mathcal{Z}_{t-p,p,N} + T^L_z \mathcal{Z}_{t,L,N} + \mathcal{E}_{t,L,N} \]

Define the residual and its statistic

\[ \mathcal{Y}_{t,L,N} \approx H^L_p \cdot \mathcal{Z}_{t-p,p,N} + T^L_z \mathcal{Z}_{t,L,N} + \mathcal{E}_{t,L,N} \]

\[ r_{ficsi}^{k,L} = \left( I - T^L_y \right) y_{k,L} - T^L_u u_{k,L} - H^L_p z_{k-L,p} \]

\[ r_{k,L} \sim \begin{cases} \mathcal{N}(0, \Sigma^L_e), & \text{fault free,} \\ \mathcal{N}(\varphi_f, \Sigma^L_e), & \text{faulty.} \end{cases} \]

\[ \Sigma^L_e = I_L \otimes \Sigma_e \text{ is the innovation covariance. } \varphi_f \text{ depends on additive faults.} \]
Cautious FICSI

FICSI

\[ \hat{r}_{k,L} = y_{k,L} - \hat{T}_y^L y_{k,L} - \hat{T}_u^L u_{k,L} - \hat{H}_2^{L,P} z_{k-L,p} \]

\[ \hat{\Xi} = \mathcal{Y}_{t,1,N} \mathcal{Z}_i^\dagger \]

\[ \text{Cov}(\hat{r}_{k,L}) \approx \left[ \mathcal{Z}_p^T \left( \mathcal{Z}_i \mathcal{Z}_i / N^T \right)^{-1} \mathcal{Z}_p \right] \otimes \hat{\Sigma}_e \]

**Scalar Example**

\[ \hat{r}(k) = y(k) - \hat{d}u(k) \]

\[ \hat{d} = \mathcal{Y}_{t,1,N} \mathcal{U}_{t,1,N}^\dagger \]

\[ \text{Cov}(\hat{r}(k)) = \left\{ \frac{u^2(k) \hat{\sigma}_e^2}{\mathcal{U}_{t,1,N} \mathcal{U}_{t,1,N}^T / N} \right\} + \hat{\sigma}_e^2 \]

**Remark:** The residual \( \hat{r}_{k,L} \) has a bias!
FDI of VTOL

- inputs: collective pitch, longitudinal cyclic pitch;
- outputs: horizontal velocity, vertical velocity, pitch rate, and sum of vertical velocity, pitch rate, and pitch angle.
- discretized for $T_s = 0.5$ seconds,
- process and measurement noise, $w(k), v(k)$: zero mean white noise, with $Q_w = 0.25 \cdot I_4$ and $Q_v = 2 \cdot I_2$. 
Identification experiment

- closed-loop experiment with $N = 2000$, $p = 20$, and

$$u(k) = - \begin{bmatrix} 0 & 0 & -0.5 & 0 \\ 0 & 0 & -0.1 & -0.1 \end{bmatrix} \cdot y(k) + \eta(k), \text{ with } \eta(k)$$

zero-mean white and $Q_\eta = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$.
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Design of experiments

Identification experiment

- closed-loop experiment with $N = 2000, p = 20$, and
  $u(k) = -\begin{bmatrix} 0 & 0 & -0.5 & 0 \\ 0 & 0 & -0.1 & -0.1 \end{bmatrix} \cdot y(k) + \eta(k)$, with $\eta(k)$

- zero-mean white and $Q_\eta = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$.

FDI design and experiment

- $p = 15, L = 10, FAR = 0.003$,
- LQG tracking control to follow a vertical velocity of 50,
- biased collective pitch control:

![Graph showing time series data with a step function at 300 time steps]
Comparison of four methods

\[ P_{ss} \] the classic model-based PSA, with \((A, B, C, D, K)\) identified by the PBSID-OPT method of Chiuso, 2007,

\[ P_{mp} \] the DD-PSA

\[ F_{no} \] the nominal data-driven FICSI method,

\[ F_{rb} \] the cautious data-driven FICSI method.
$P_{ss}$ the classic model-based PSA

![Graph showing test statistics and threshold](image.png)

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**Motivation**

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**$P_{mp}$ the data-driven PSA**

![Graph showing test statistics](image)

- **$P_{mp}$** threshold
- **test statistics**
- **samples**

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$F_{rb}$ v.s. $F_{no}$ FICSI

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Sensor/Actuator Fault Isolation with dual sensor/actuator configuration

- No voting is possible.
- We want to make use of/demonstrate the possibilities of FICSI.
- “Single” transducer failure at a particular time instant.
The wind turbine benchmark model

Three-bladed, horizontal-axial, and variable-speed wind turbine with a full converter, running in closed loop.\(^1\)

\(^1\) [Odgaard et al., 2009].
Fault Scenarios and requirements

<table>
<thead>
<tr>
<th>#</th>
<th>fault</th>
<th>duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\beta_{1,m_1}$ fixed to $5^o$</td>
<td>$2000 \sim 2100$ sec</td>
</tr>
<tr>
<td>3</td>
<td>$\beta_{3,m_1}$ fixed to $10^o$</td>
<td>$2600 \sim 2700$ sec</td>
</tr>
<tr>
<td>4</td>
<td>$\omega_{r,m_1}$ fixed to $1.4 rad/s$</td>
<td>$1500 \sim 1600$ sec</td>
</tr>
</tbody>
</table>

Requirements

- time of detection no longer than 10 sampling instants
- no missed detections
- mean time between false detection no larger than $10^5$ sampling instants
2 dual sensor case

Consider an LTI system with 2 pairs of (identical) sensors for measuring the outputs of the system.

Isolation Strategy

Let the read-out of the first pair of sensors be denoted by $S_1^1, S_1^2$, and for the second pair by $S_2^1, S_2^2$, then we determine the fault detection filter:

$$r_{ij}(k) = F_{ij}(u(k), [S_i^1(k) \ S_j^2(k)])$$

<table>
<thead>
<tr>
<th>Failing Sensor</th>
<th>$S_1^1$</th>
<th>$S_1^2$</th>
<th>$S_2^1$</th>
<th>$S_2^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_{11}$</td>
<td>$\downarrow$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$F_{12}$</td>
<td>$\downarrow$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$F_{21}$</td>
<td></td>
<td>$\downarrow$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$F_{22}$</td>
<td></td>
<td></td>
<td>$\downarrow$</td>
<td>$\downarrow$</td>
</tr>
</tbody>
</table>
Disturbances and measurement noise

- The turbine is disturbed by unknown wind speed $V_w$.

- The variance of the measurement noise in the sensors, denoted as $\sigma^2_\star$, is respectively defined as:

$$
\begin{align*}
\sigma^2_{\beta_1,m_1} &= \sigma^2_{\beta_1,m_2} = \sigma^2_{\beta_2,m_1} = \sigma^2_{\beta_2,m_2} = \sigma^2_{\beta_3,m_1} = \sigma^2_{\beta_3,m_2} = 0.2, \\
\sigma^2_{\omega_g,m_1} &= \sigma^2_{\omega_g,m_2} = 0.05, \\
\sigma^2_{\omega_r,m_1} &= \sigma^2_{\omega_r,m_2} = 0.0251.
\end{align*}
$$
Experimental Conditions

- Wind speed profile set to the mean of the real measured wind data, i.e. $D_{\text{v\_wind}} \equiv 12.3$ in the SimuLink model, “BenchMark.mdl”.
- No extra excitation signals were added to this model.
- We only used the data from the first 200 seconds, i.e. $N = 2 \times 10^4$.
- The horizons of the Fault Detection filters were chosen as $p = 60$, $L = 50$ and the FAR was set to 0.001.
- We only selected three output channels for the identification, i.e. $\beta_1,m_1, \omega_r,m_1, \omega_g,m_1$. The two input channels are $\beta_r, \tau_g$. 
Example: test statistics of filter $\mathcal{F}_3$
Tak for opmrksomheden