



Energy-SmartOps

Integrated Control and Operation of Process, Rotating Machinery and Electrical Equipment

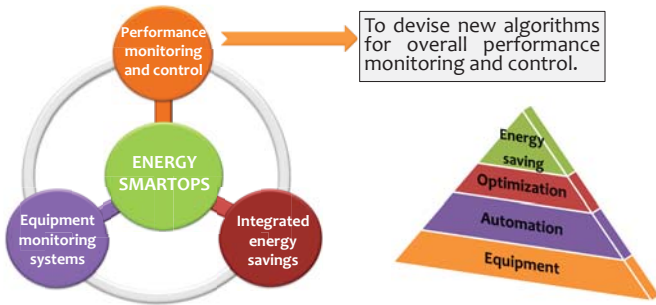
MULTIVARIATE STATISTICAL PROCESS MONITORING

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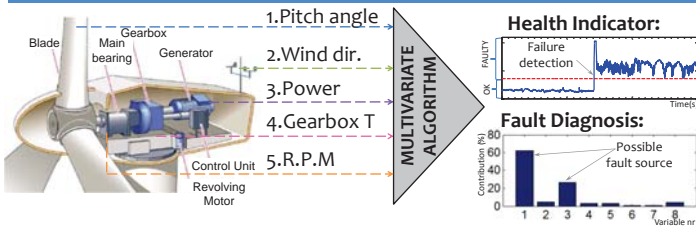
1. My Project in SmartOps



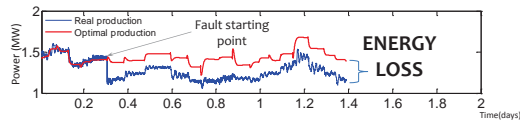
WORK PACKAGE 3: MAINTENANCE AND DIAGNOSIS

ESR-D	ESR-H	ESR-I
Multivariate statistical process predictive monitoring using operational data.	Interconnections between process, mechanical and electrical equipment.	Reactive performance-based maintenance planning for process plants.

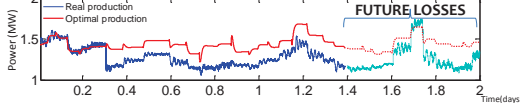
2. Problem Statement



Performance degradation:



Prediction of fault evolution:



3.1 Methodology: Canonical Variate Analysis

- **Data driven:** Not based on first principle equations.
- **Multivariate:** Takes into account correlation between variables.
- **Dimensionality reduction:** Selection of the most relevant information.
- **Fault detection:** A scalar statistic (Q , T^2) can characterize multi-dimensional data variability.
- ✓ **Dynamic:** Time correlation.
- ✓ **State-space based:** More suitable for dynamic monitoring.
- ✓ **System identification:** By linear regression using process data.
- ✓ **Nonlinearities:** Estimation of actual probability density functions through kernel density estimations.

Mathematical Procedure:

$$[y_1, y_2, y_3, y_4, y_5, y_6, y_7, y_8, y_9, y_{10}, \dots, y_n]$$

$$y_{p,k} = \begin{bmatrix} y_k \\ y_{k-1} \\ \vdots \\ y_{k-p+1} \end{bmatrix} \quad y_{f,k} = \begin{bmatrix} y_{k+1} \\ y_{k+2} \\ \vdots \\ y_{k+f} \end{bmatrix}$$

Covariance Matrices:

$$\Sigma_{pp} = \frac{1}{M-1} Y_p Y_p^T \quad \Sigma_{ff} = \frac{1}{M-1} Y_f Y_f^T \quad \Sigma_{pf} = \frac{1}{M-1} Y_p Y_f^T$$

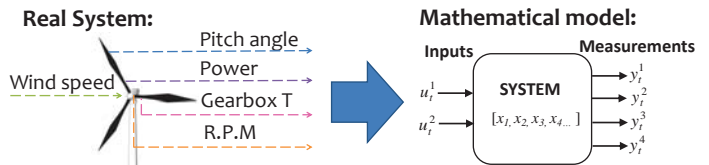
Hankel Matrix:

$$H = \sum_{i=1}^L \sum_{j=1}^{L-i+1} \Sigma_{pp}^{-i/2} = UDV^T \quad \begin{cases} UU^T = VV^T = I \\ D_{i,i} = 0 \text{ if } (i \neq j) \end{cases}$$

Canonical variates and indicator:

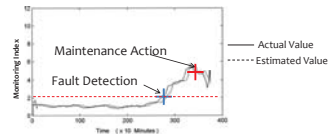
$$J = V^T \Sigma_{pp}^{-1/2} \quad z = J \cdot Y_p \quad T_j^2 = \sum_{i=1}^{j-1} z_i^2$$

3.2. CVA for System Identification

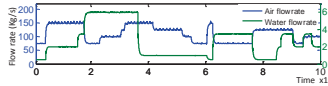


$$\text{Linear state-space model: } \begin{cases} x_{t+1} = \Phi x_t + G u_t + w_t \\ y_t = H x_t + A u_t + B w_t + v_t \end{cases}$$

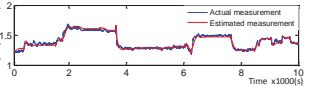
$$m_t = J y_{p,t} \quad \begin{pmatrix} \Phi & G \\ H & A \end{pmatrix} = \text{cov} \left[\begin{pmatrix} m_{t+1} \\ y_t \end{pmatrix} \right] \cdot \text{cov}^{-1} \left[\begin{pmatrix} m_t \\ y_t \end{pmatrix} \right]$$



System input:

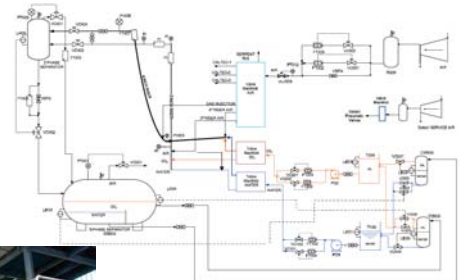


Measurement estimation:



4. Model Validation: Experimental Data

Experimental data was acquired in the 3 phase test rig at Cranfield University. Real faults were introduced in the system to obtain performance data under faulty conditions.



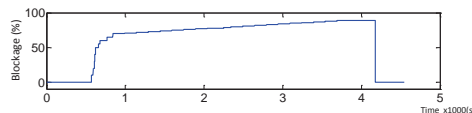
3 phase flow facility:



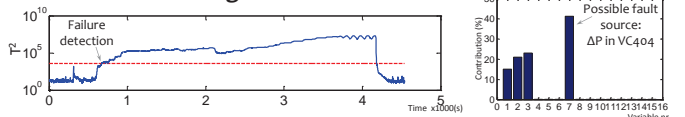
- 4" Flow loop (55 m long 2° inclined pipeline, 10.5m catenary shaped riser)
- Maximum pressure: 7 barg
- Air supply: Up to 1410 m³/hr @ 7 barg
- Water supply: Up to 100 m³/hr @ 10 barg
- Controlled by Delta V

5. Results (Blockage in top separator intake)

Fault evolution:



Fault detection and diagnosis:



Energy waste estimation:

