



# Energy-SmartOps

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

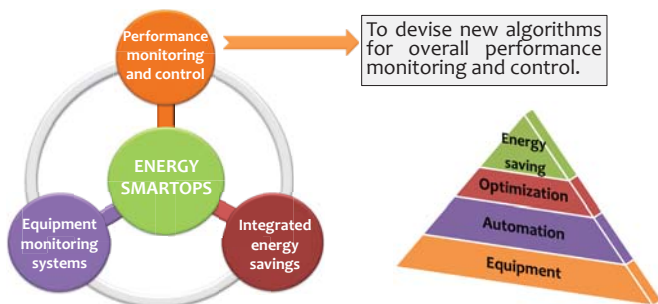
## MULTIVARIATE STATISTICAL PROCESS MONITORING

ESR-D Cristóbal Ruiz Cárcel; supervised by Prof. David Mba and Dr. Yi Cao

email: c.ruizcarcel@cranfield.co.uk

School of Engineering, Cranfield University; Bedfordshire MK43 0EX, UK

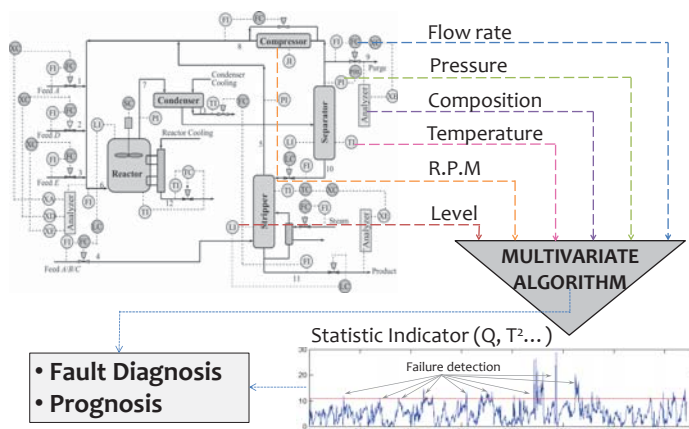
### 1. My Project in SmartOps



#### 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



### 3. 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:

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

↑ Time k

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

#### Covariance Matrices:

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

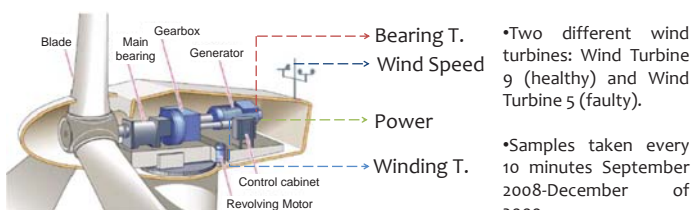
#### Hankel Matrix:

$$H = \Sigma_{ff}^{-1/2} \Sigma_{pp}^{-1/2} = U D V^T \quad \begin{cases} U U^T = V V^T = I \\ D_{i,j} = 0 \text{ if } (i \neq j) \end{cases}$$

#### Canonical variates and indicator:

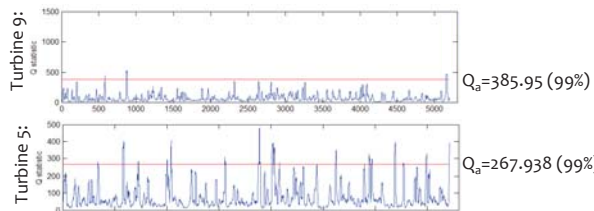
$$J = V_f^T \Sigma_{pp}^{-1/2} \quad z = J \cdot Y_p \quad T_j^2 = \sum_{i=1}^{i=r} z_{i,j}^2$$

### 4. CVA Application Example: Wind Turbine Data



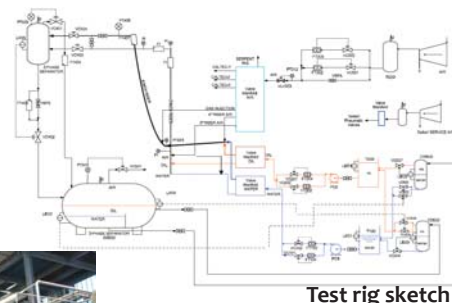
• Two different wind turbines: Wind Turbine 9 (healthy) and Wind Turbine 5 (faulty).

• Samples taken every 10 minutes September 2008-December 2009.



### 5. Model Validation: Experimental Data

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

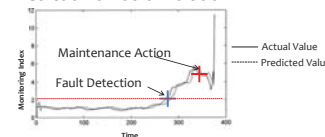


The results obtained in those experiments will be made available for other ESR's working in the field of condition monitoring, constituting the Cranfield case study.

### 6. Future Work

#### Theoretical Work:

Prediction of fault Evolution:



Linear state-space model:  $\begin{cases} x_{k+1} = \Phi x_k + G u_k + w_k \\ y_k = H x_k + A u_k + B w_k + v_k \end{cases}$

$$m_t = J y_{p,t} \quad \begin{bmatrix} m_{t+1} \\ y_t \end{bmatrix} = \begin{bmatrix} \Phi & G \\ H & A \end{bmatrix} \begin{bmatrix} m_t \\ u_t \end{bmatrix} + \begin{bmatrix} I & 0 \\ B & I \end{bmatrix} \begin{bmatrix} w_t \\ v_t \end{bmatrix}$$

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

#### Development and implementation of MVA for Condition Monitoring:

- ✓ Develop Fault and Prognostic Algorithms (FAPA) based on informed literature.
- ✓ Validation and optimization of the models using experimental data.
- ✓ **Secondment in ABB-DE:**
  - ✓ Refine models based on observations of on-site data.
  - ✓ Develop software tool integrating models developed with maintenance protocols and strategies for industrial use.

