# Detection and diagnosis of plant-wide disturbances

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A UCL Member of the Imperial College/UCL Centre for Process Systems Engineering

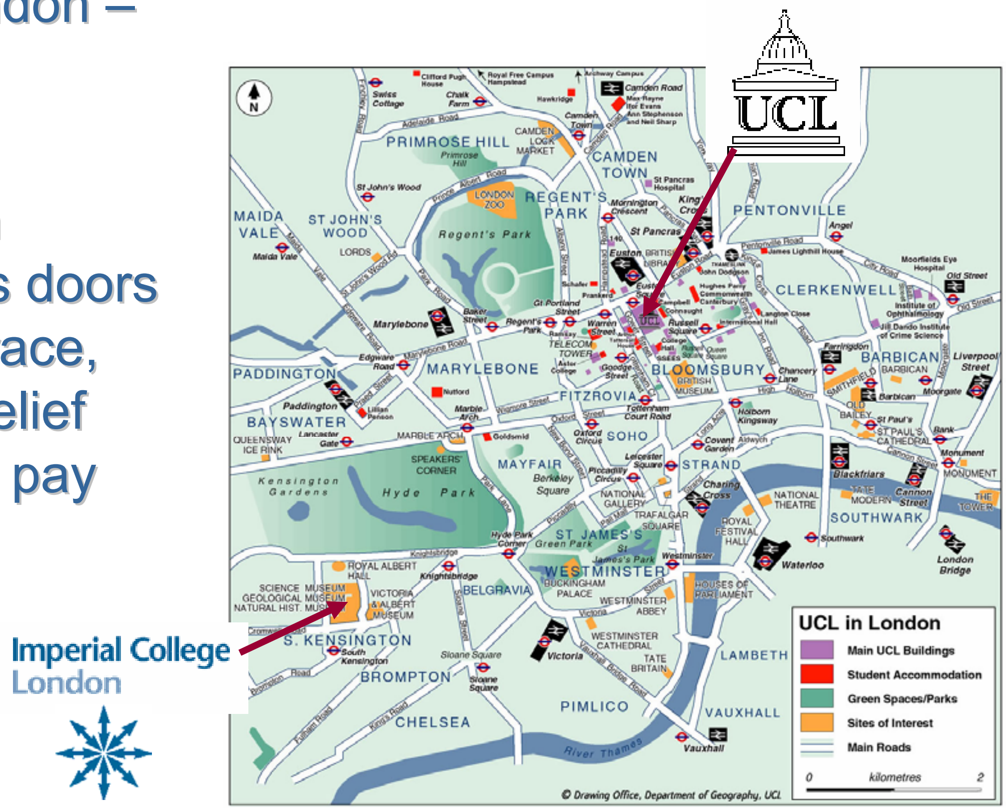
# University College London (UCL)



## UCL

Is in the heart of London – postcode is WC1;

Was the first English University to open its doors to all, regardless of race, religion or political belief (provided they could pay the fees).

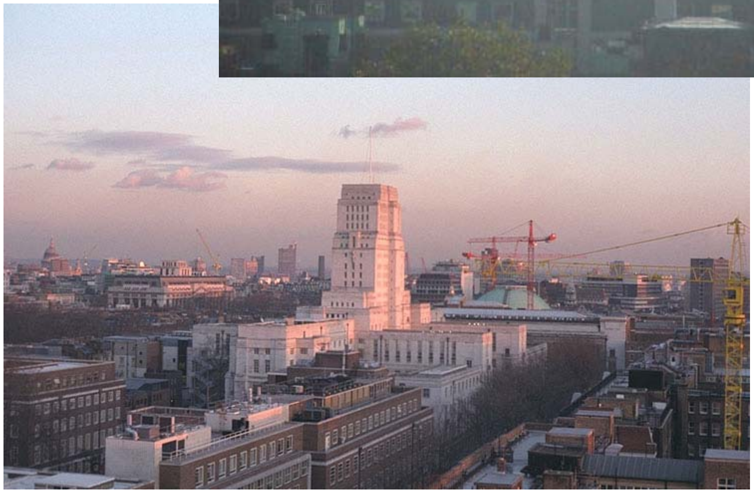


# University College London (UCL)



## UCL E&E Eng

The thermionic valve, which made radio and modern electronics possible, was invented in E&E Engineering.



Views courtesy of Paul Brennan and Kevin Lee

# Layout of the presentation



Plant-wide disturbances

- Examples

Detection and characterization

- Multiple oscillation detection
- Clustering methods

Isolation and diagnosis of the root cause

- Non-linearity tests
- Cause and effect analysis
- Single loop tests
- Open issues in diagnosis

Tools for users

Useful literature

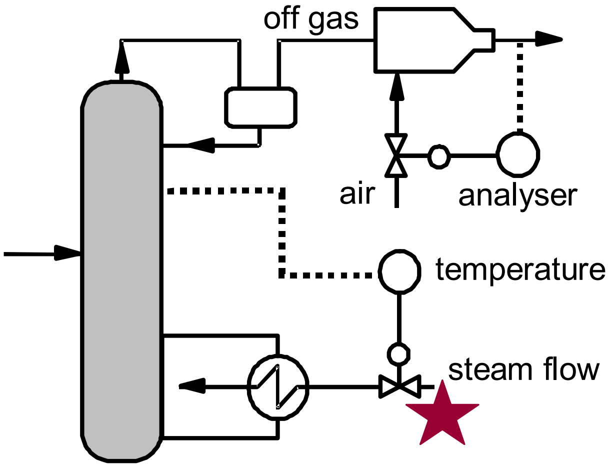
# Distributed plant-wide disturbances

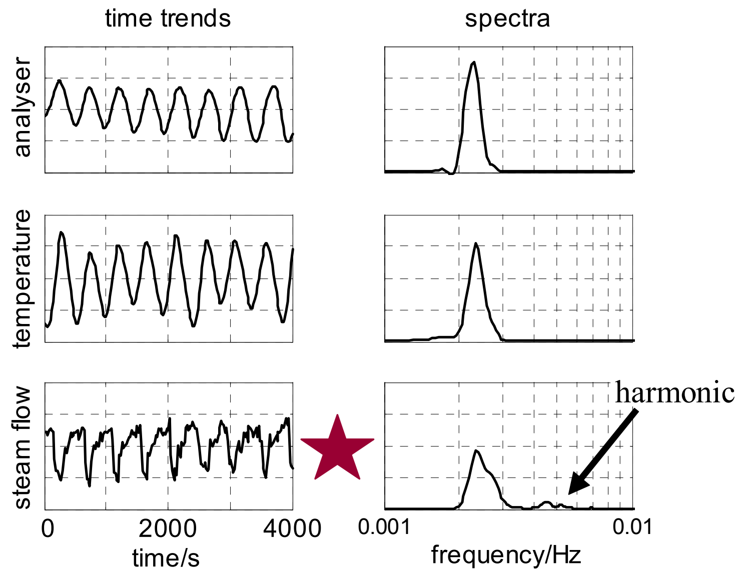
# Distributed disturbances



## Example

- Faulty steam flow sensor

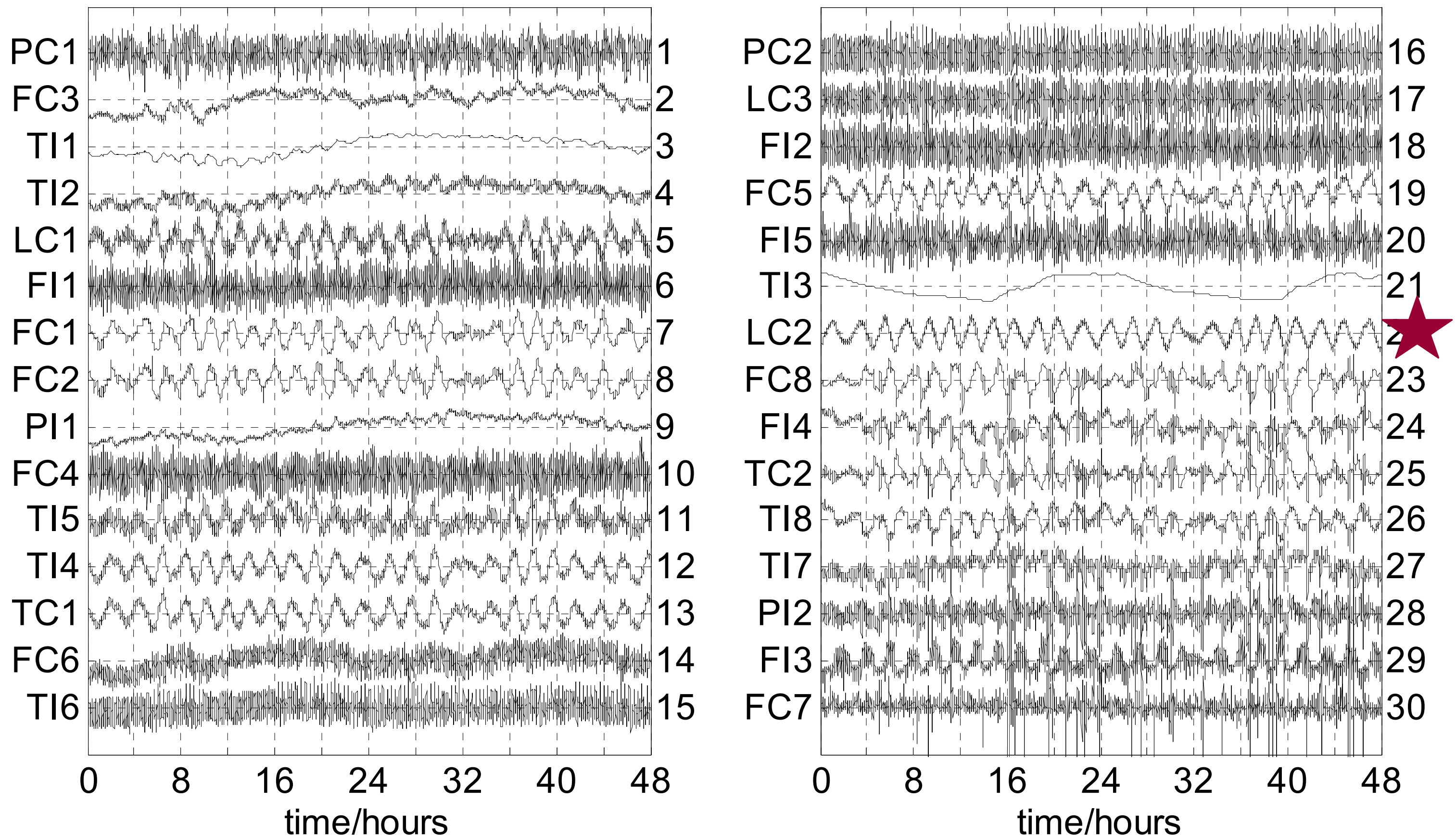


# Distributed disturbances

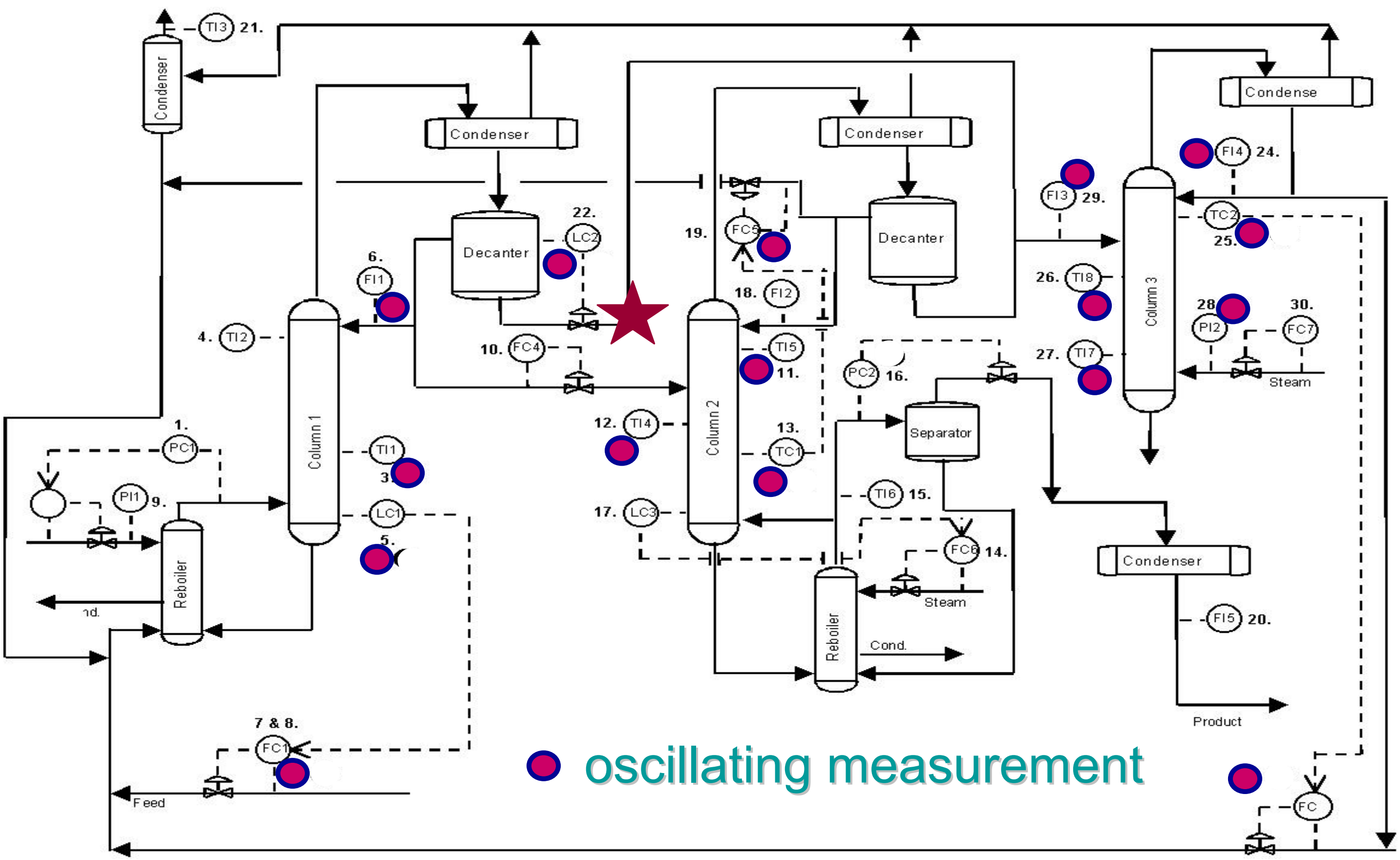
## Example (Eastman Chemical Company)

- Sticking valve



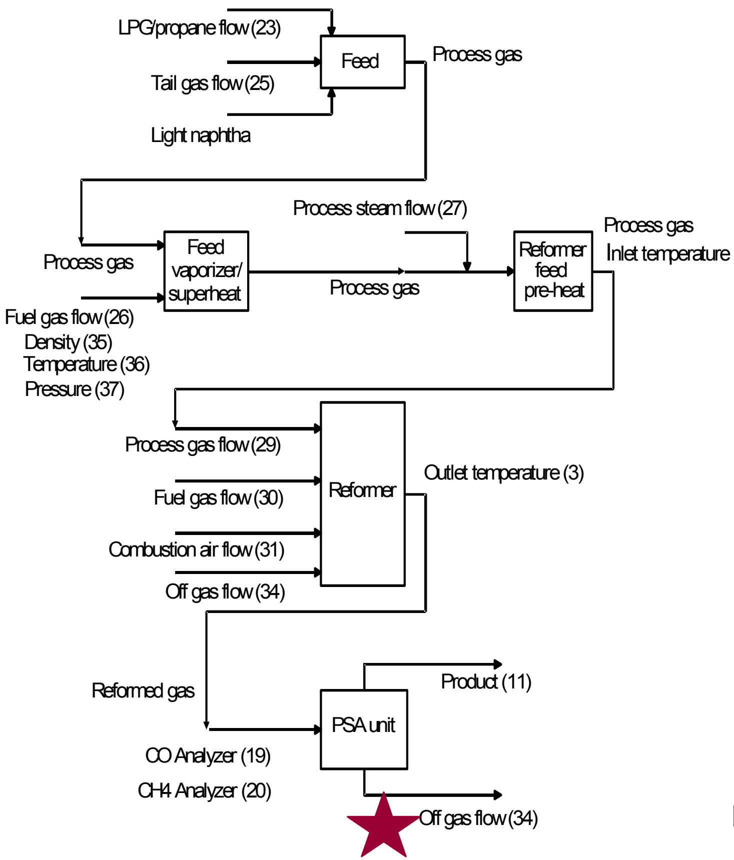
# Distributed disturbances

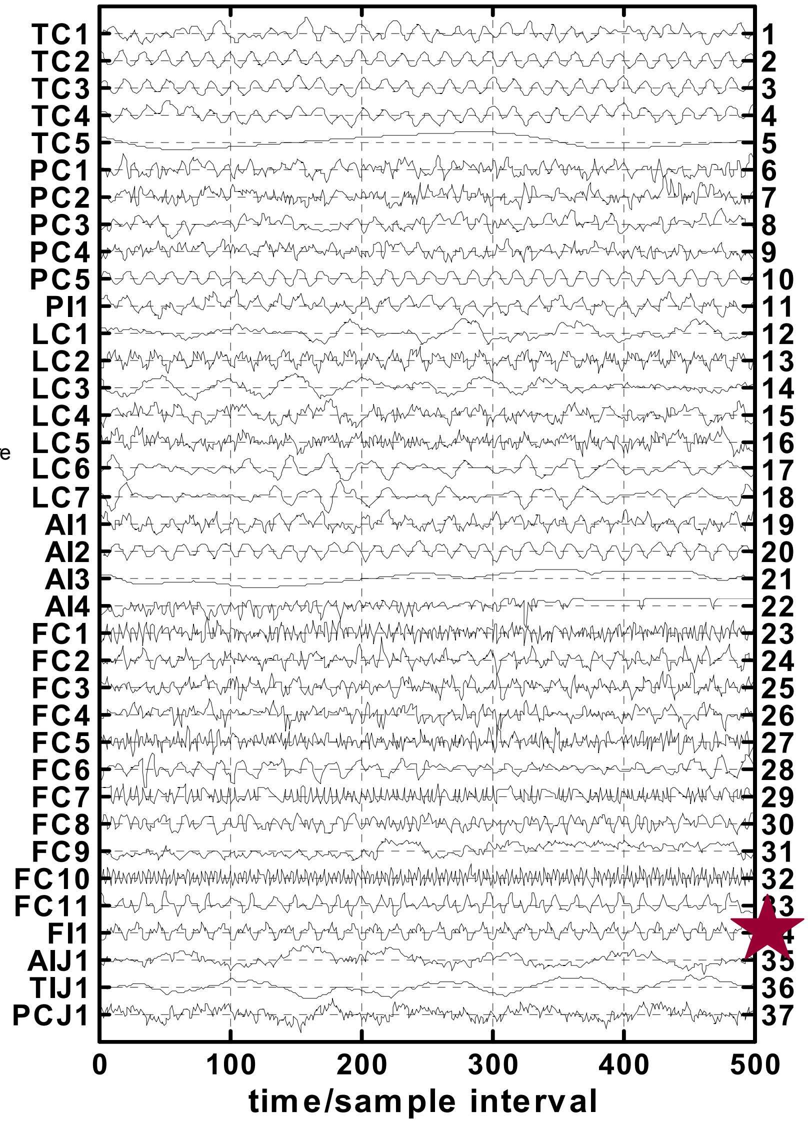




# Example (SE Asia data)

- Valve problem



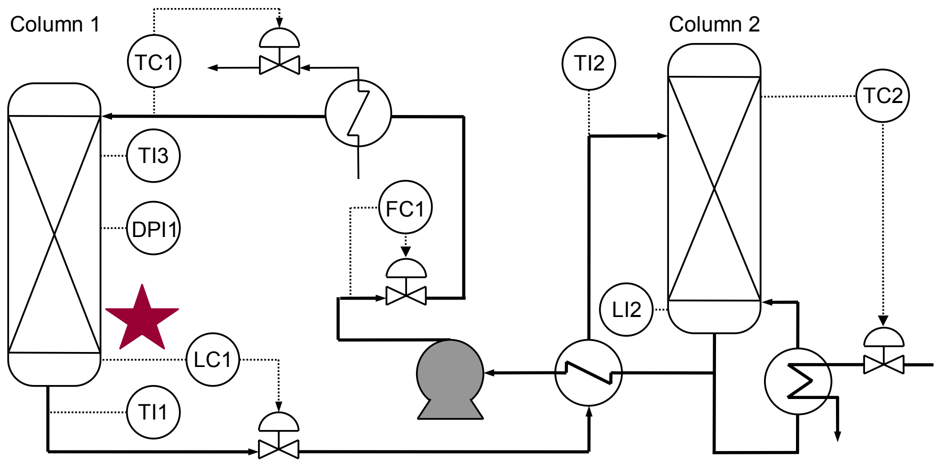



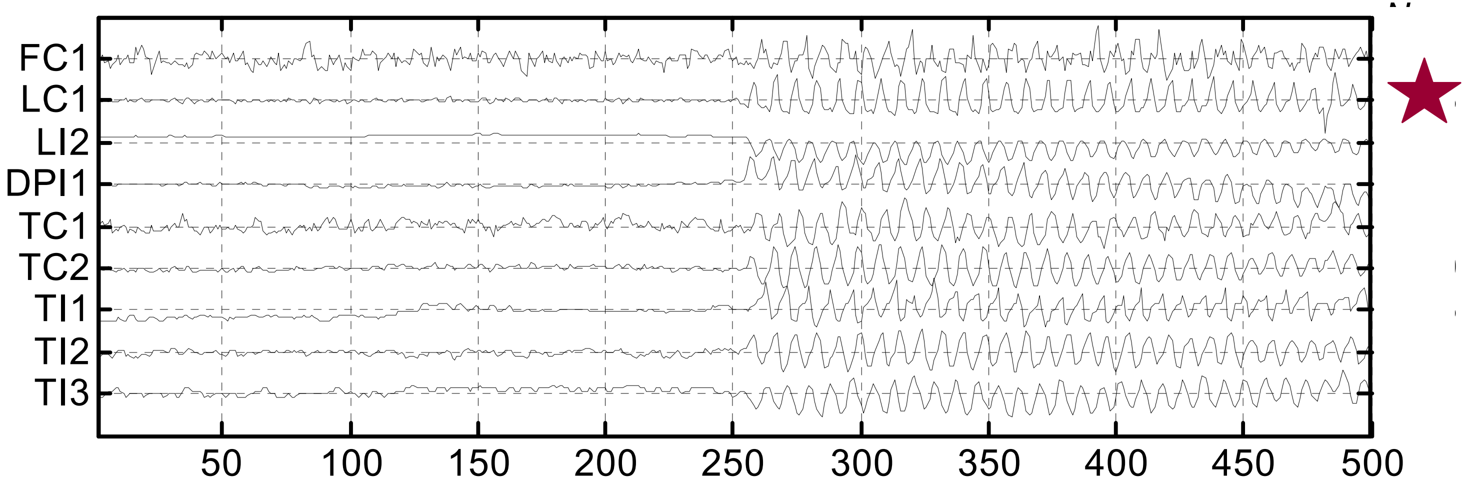
# Distributed disturbances



## Example (BP)

- foaming

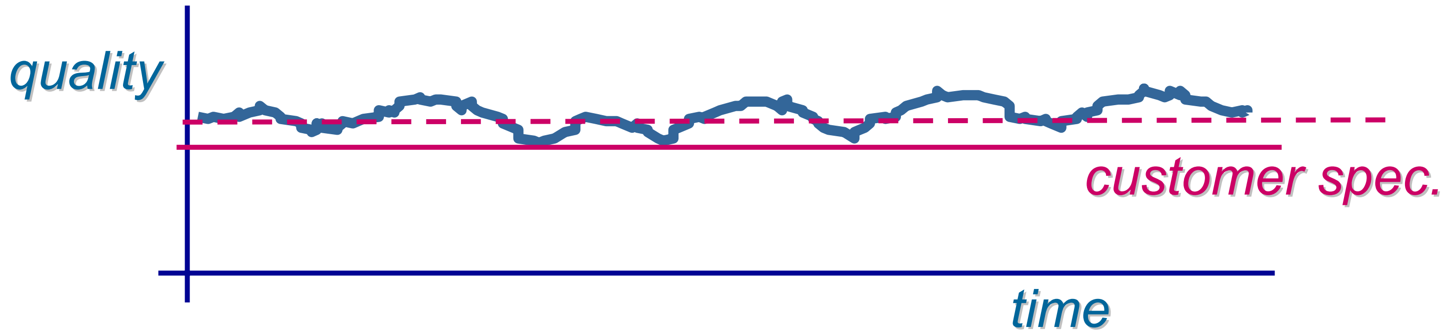


# Distributed disturbances

## Why is it important?

- Chemical plants make most money when they are running steadily without disturbance (Shunta,1995);




- But diagnosing and rectifying the source of a disturbance has costs;
- Therefore methods are needed to aid detection and diagnosis of the root cause during normal running.

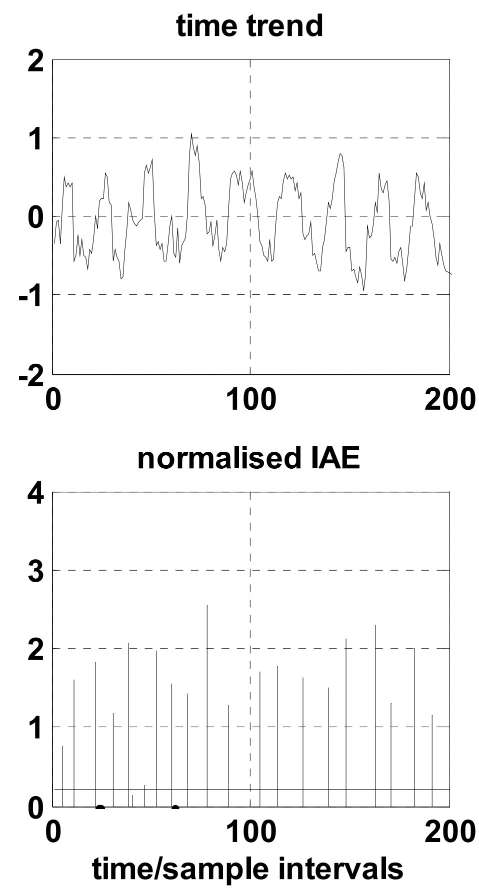
# Detection of distributed disturbances: Oscillation detection

Hägglund, T., 1995, A control-loop performance monitor, *Control Engineering Practice*, 3, 1543-1551.
Thornhill, N.F., Huang, B., and Zhang, H., 2003, *Journal of Process Control*, 13, 91-100.

# Oscillation detection

The original zero crossings method was by Tore Hägglund (1995)

- Zero crossing detection;
- Calculation of integrated absolute error (IAE);
- Comparison with a threshold to make a decision;
- Can be used on-line.

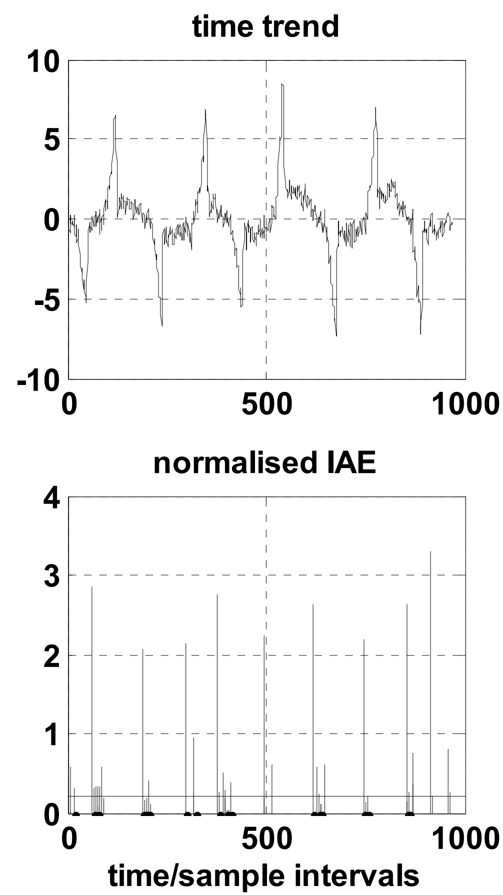


# Oscillation detection

## Original zero crossings method

- It's not so suitable for quantifying the oscillation parameters;
- Regular zero-crossings suggest an oscillation;
- But noisy time domain has spurious zero crossings;
- One possibility is to set threshold higher;

or …..



# Oscillation detection

## Plant-wide oscillation detection

- Use detection of zero crossings of autocovariance functions – autocovariance is much smoother:

$$ACF(\tau) = \frac{1}{N-(\tau+1)} \sum_{i=\tau+1}^{N} y(i) \times y(i-\tau)$$

$$\textit{where} \quad y \ \textit{is mean} - \textit{centered and scaled}$$

- The ACF method is suitable for use with historical data because the calculation uses a batch of data.

# Oscillation detection



## Plant-wide oscillation detection

- Find the mean ($T_p$) and standard deviation ($\sigma_{\Delta Tp}$) of intervals between zero crossings;
- Oscillation index is:

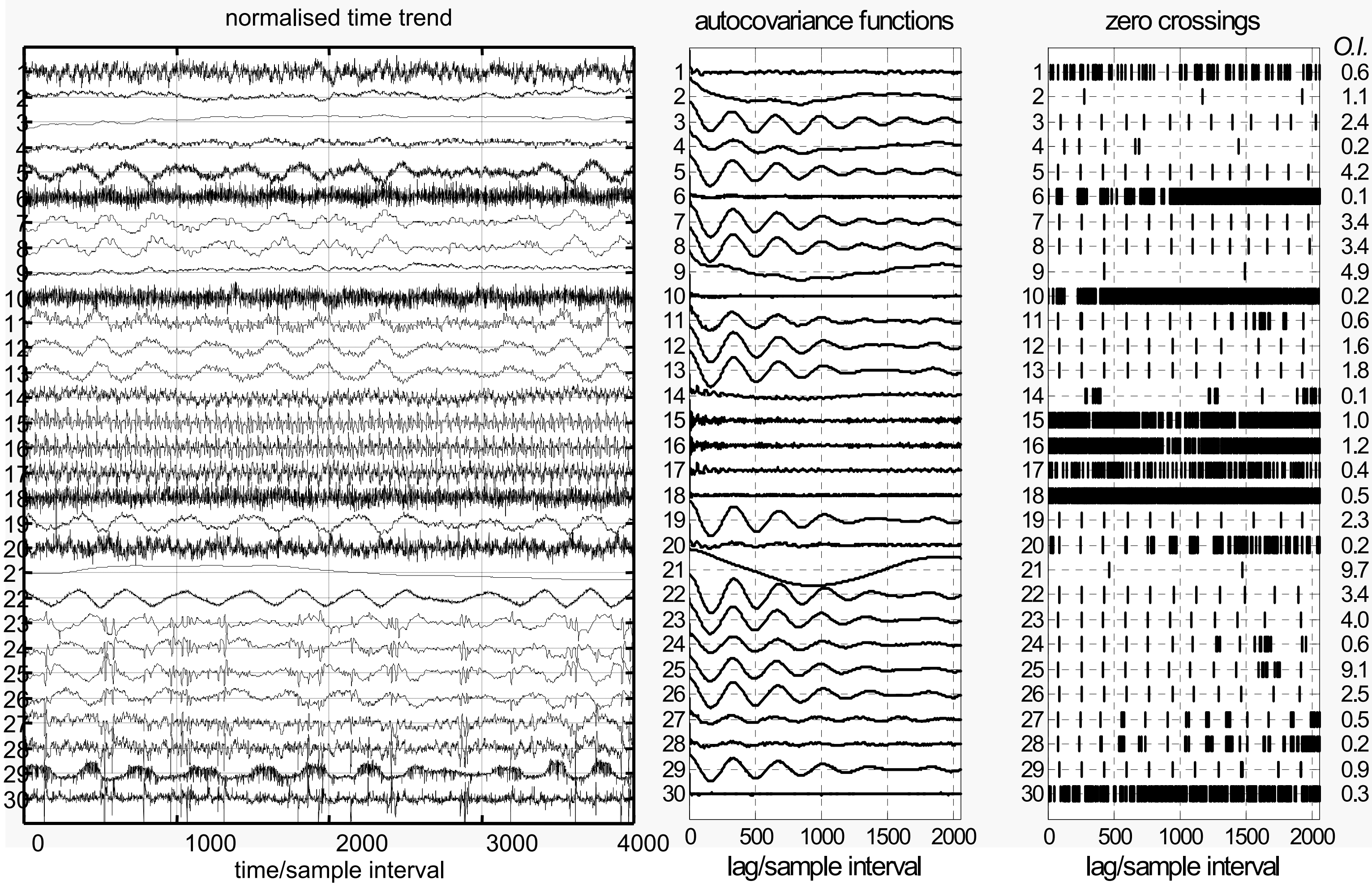
$$O.I = \frac{T_p}{3\sigma_{\Delta T_p}}$$

- Random zero crossings have exponential distribution:

$$T_p = \sigma_{\Delta T_p}$$

- So *OI* >1 is a 3-sigma rejection of the null hypothesis of random zero crossings.

# Oscillation detection



# Oscillation detection



## Oscillation results

**Plant-wide analysis**

| ave_period | tags involved |
| --- | --- |
| 17.67 | 16 15 |
| 347.9 | 25 5 23 7 22 8 26 19 13 12 |
| 1384 | 2 |

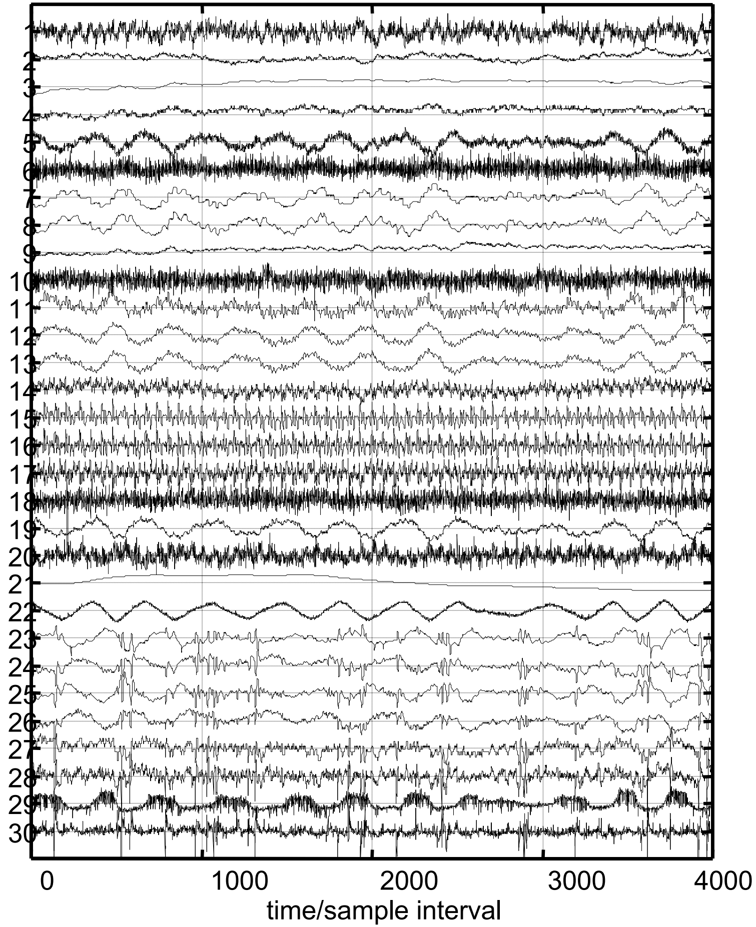
# Detection of distributed disturbances: Spectral principal component analysis

Thornhill, N. F., Shah, S.L., Huang, B., and Vishnubhotla, A., 2002, Spectral principal component analysis of dynamic process data, *Control Engineering Practice*, 10, 833-846.

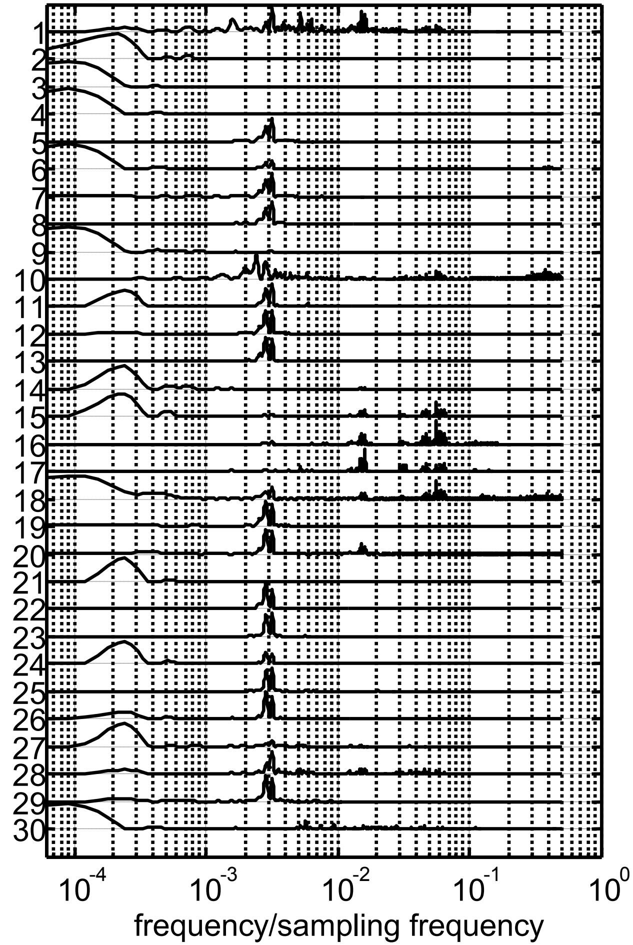
# Spectral PCA



normalised time trend




spectra



# Spectral PCA



## Spectral PCA

- The challenge is to automate detection of tags characterized by similar disturbances;
- Their spectra will be similar;
- Spectra are invariant to time delays and lags;
- Spectral PCA is better than time domain PCA for dynamic data, even if time shifting is used;
- Spectral methods can’t be used in real time.

# Spectral PCA

Use FFT to derive power spectra.

***X*** is matrix of spectra, 30 rows and 4196 columns.

*4196 frequencies*

*30 spectra, one for each tag*

## Method

- Decompose ***X*** as a sum over basis functions ***X*** = ***T*** x ***P′***
- The ***T*** vectors are the scores. The basis functions are the rows of the loadings matrix ***P′***

# Spectral PCA



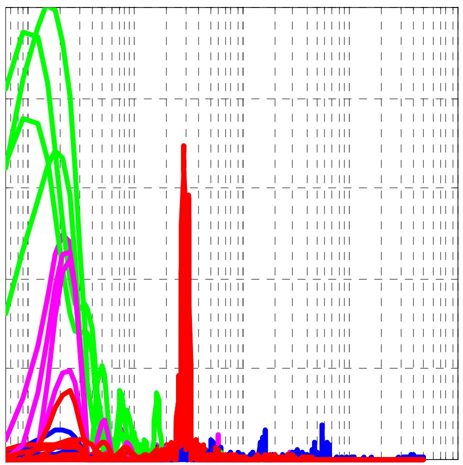
e.g. For a 3 - PC model:

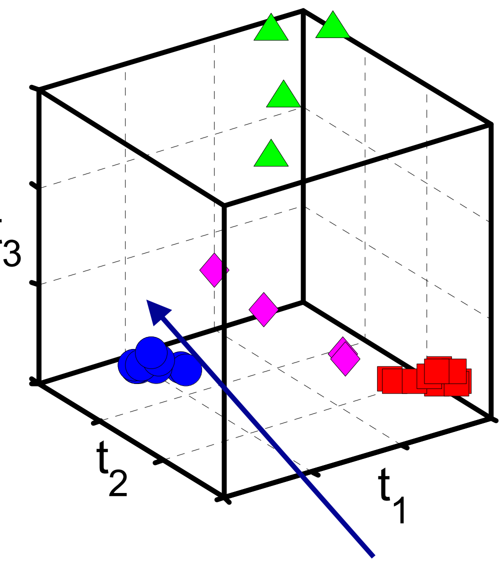
$$\boldsymbol{X} = \begin{pmatrix} t_{1,1} \\ \dots \\ t_{m,1} \end{pmatrix} \boldsymbol{p}'_1 + \begin{pmatrix} t_{1,2} \\ \dots \\ t_{m,2} \end{pmatrix} \boldsymbol{p}'_2 + \begin{pmatrix} t_{1,3} \\ \dots \\ t_{m,3} \end{pmatrix} \boldsymbol{p}'_3 + \boldsymbol{E}$$

- The *n*'th spectrum has scores $t_{n,1}$, $t_{n,2}$ and $t_{n,3}$ . These are the weights in the summation of the ***p*´**- vectors needed to approximately reconstruct the *n*'th spectrum;
- Process tags with similar spectra have similar *t*-values;
- Clusters represent process tags with similar spectra.

# Spectral PCA

## Visual colour coding:



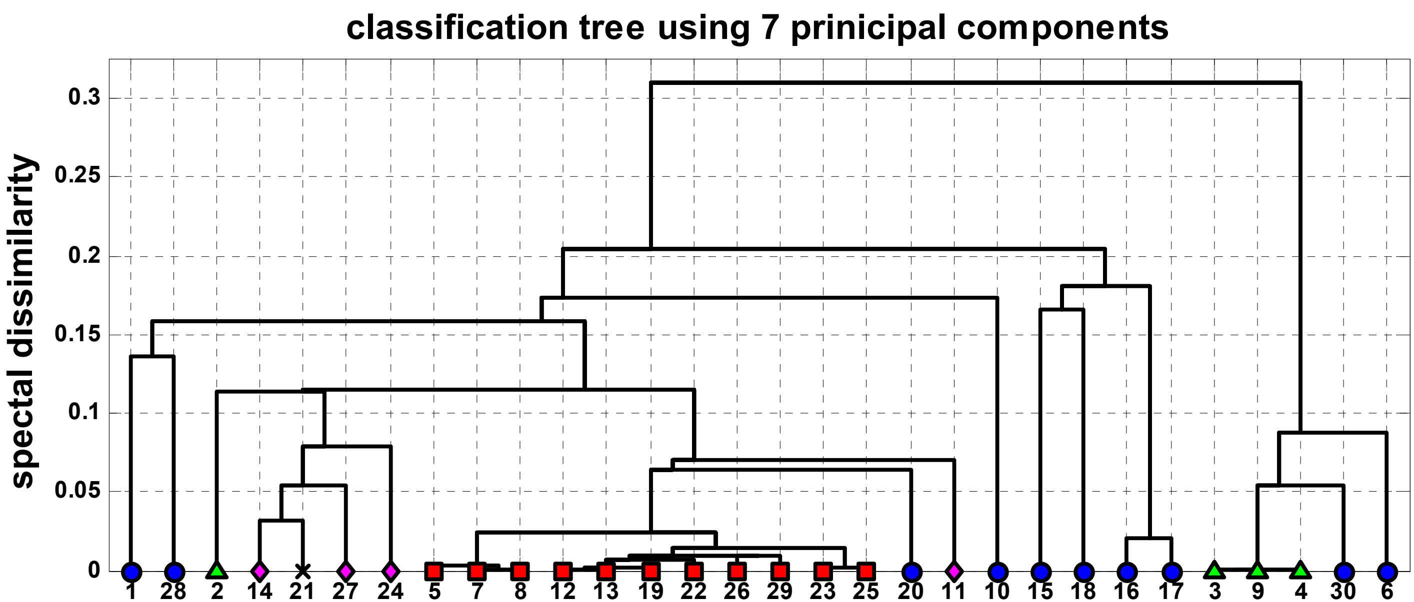




*origin {0,0,0} is here*

# Spectral PCA

## Analysis with seven PCs

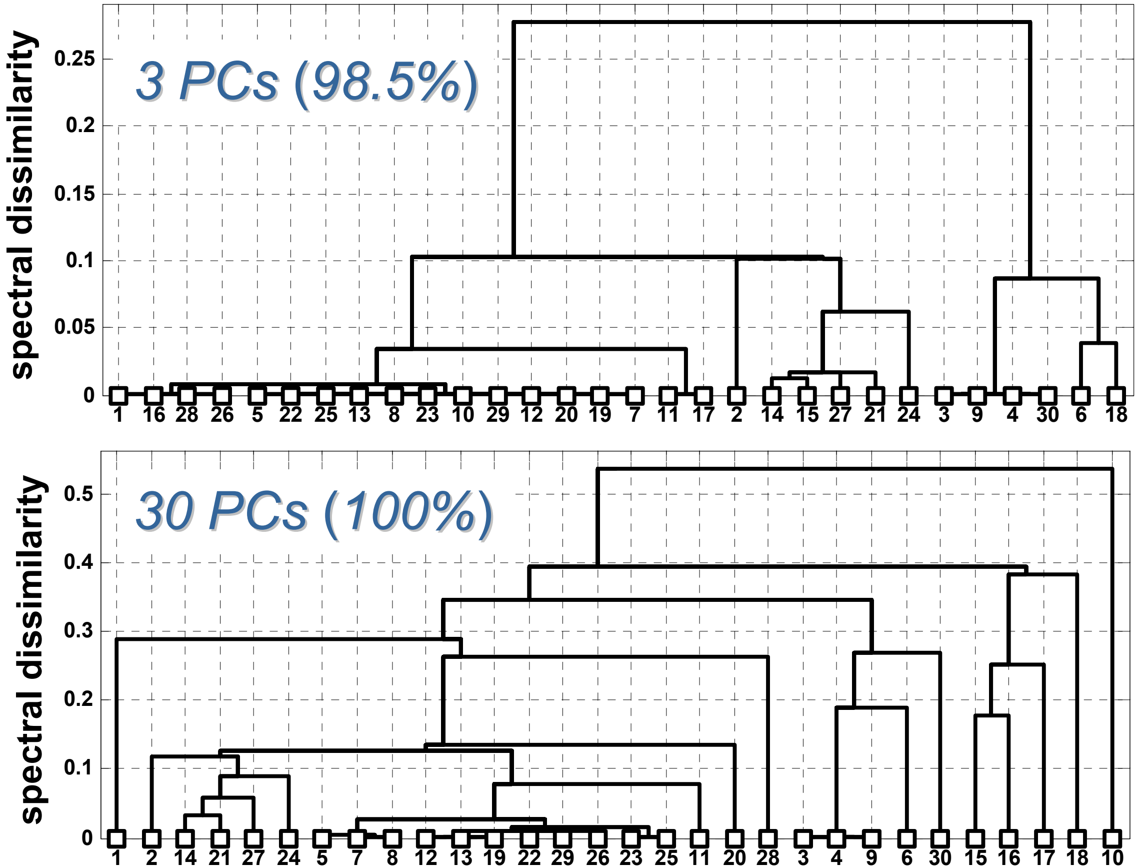
- The vertical axis is a measure of how unalike the *t*'s are;
- The tree gives more insight than can be seen in 3-D;
- Some visual selections were wrong, e.g. 2, 21, 11



# Spectral PCA

## Effect of different numbers of PCs

| *N* | *Var%* |
|---|---|
| 1 | 47.12 |
| 2 | 75.29 |
| 3 | 98.51 |
| 4 | 98.99 |
| 5 | 99.33 |
| 6 | 99.58 |
| 7 | 99.71 |
| 8 | 99.78 |
| 9 | 99.82 |
| 10 | 99.85 |
| 11 | 99.88 |
| 12 | 99.90 |



# Spectral PCA

## Effect of different numbers of PCs

- Small numbers of PCs enhance the clusters.
- Some tags may be wrongly classified, e.g. tag 10, because some features are overlooked with too few PCs;
- When all PCs are used every minor feature is captured;
- Clusters are not tight when all PCs are used;
- If there is a cluster when all PCs are used then it is a *really important cluster*.

# Detection of distributed disturbances: Spectral independent component analysis

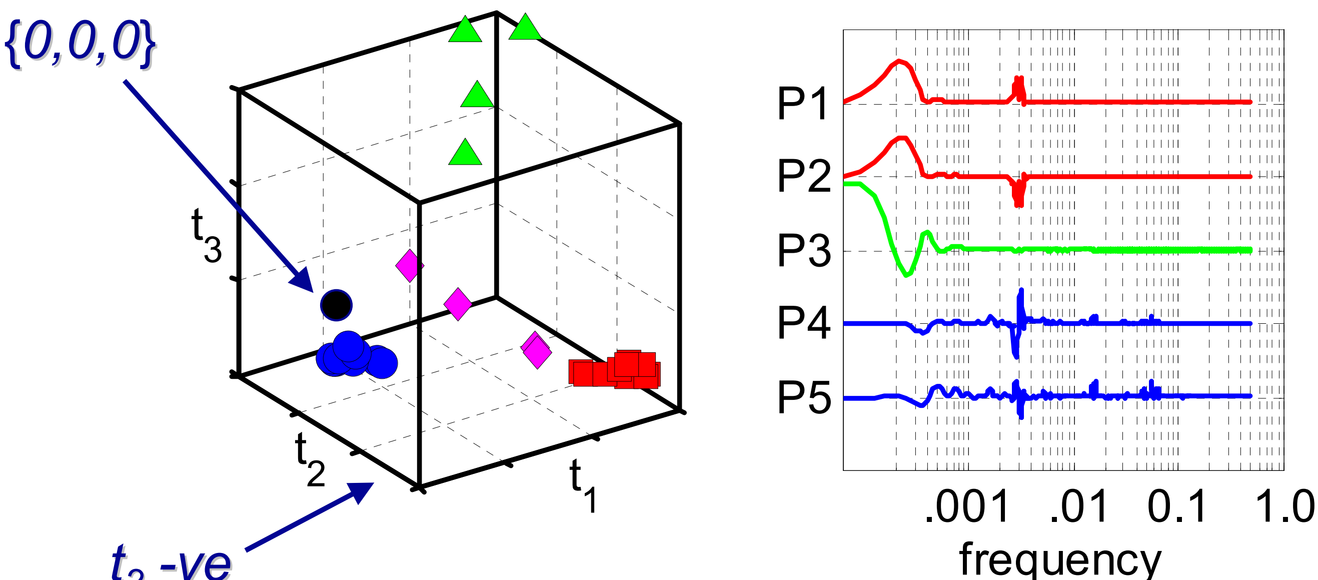
Xia, C., 2003, *Control Loop Measurement Based Isolation of Faults and Disturbances in Process Plants*, PhD Thesis, University of Glasgow, 2003.

Xia, C., and Howell, J., 2005, Isolating multiple sources of plant-wide oscillations via independent component analysis, *Control Engineering Practice*, 13, 1027-1035.

# Spectral ICA

## Reconstruction of spectra using *X* = *T* x *P´*

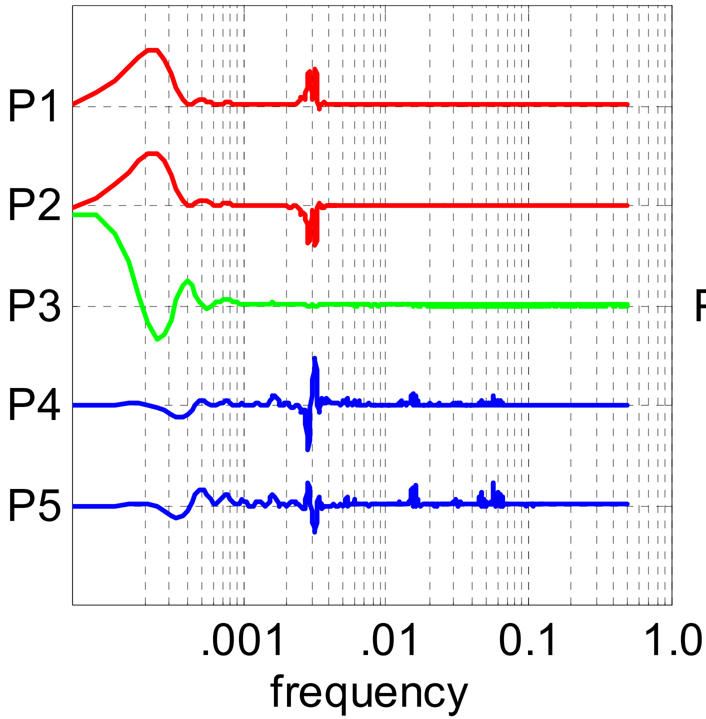
- For instance, red spots are P1 - P2;
- Blue spots are P4+P5. They are near origin in a 3-PC plot.



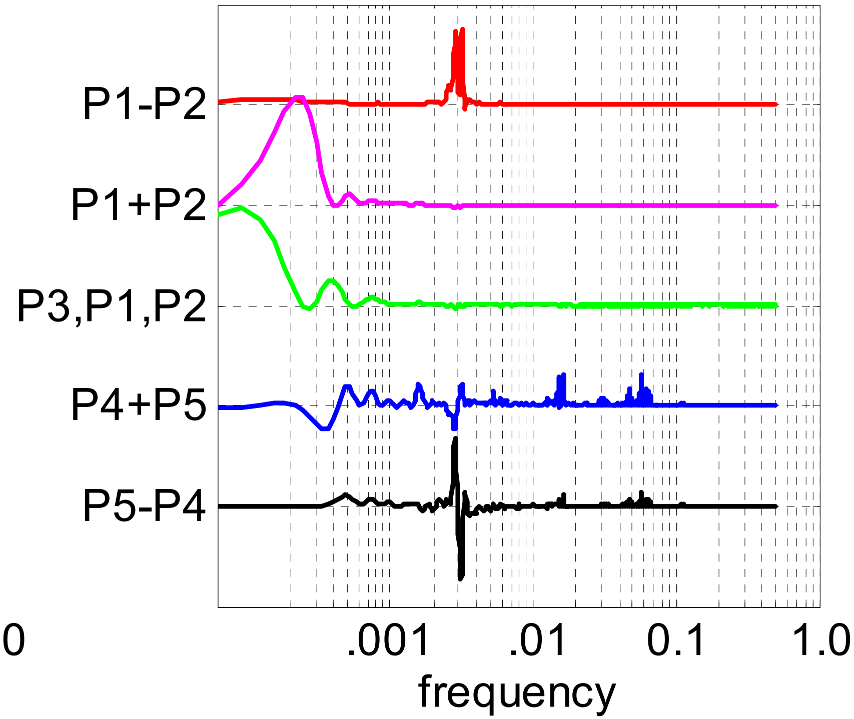

*score plot* *loading vector plots*

# Spectral ICA

## Linear combinations can separate the peaks




*loading plot*




*linear combinations of loadings*

# Spectral ICA

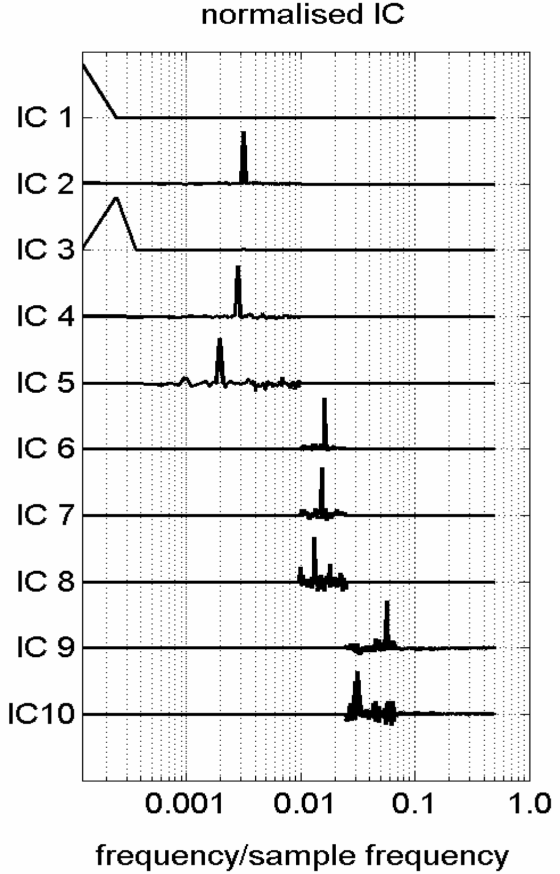


## Spectral ICA

- Implemented by Xia, University of Glasgow as an extension to spectral PCA:

$$\Pr(X_1, X_2) = \Pr(X_1)\Pr(X_2)$$

- where Pr(X) is the probability density function;
- PCA loadings are orthogonal but not independent;
- ICA loadings are independent and each has a unique peak like the sums and differences of PCA loadings.



# Detection of distributed disturbances. Spectral correlation analysis

Tangirala, A.K., Shah, S.L., and Thornhill, N.F., 2005, PSCMAP: A new measure for plant-wide oscillation detection, *Journal of Process Control*, *accepted for publication*.

# Spectral correlation analysis

## Spectral correlation and colour map

- Devised by Arun Tangirala, University of Alberta and IIT Madras;
- Simpler calculation than spectral PCA, it determines correlation between one spectrum and another;
- Visualization: A colour map shows the tags with strong spectral similarity;
- The result is theoretically identical to using all spectral PCs.

# Spectral correlation analysis

- The correlation coefficient for data *x* and *y* is:

$$\sigma_{x,y} = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{x}_i\,\hat{y}_i\right)$$

$$\textit{where} \quad \hat{x}_i = \frac{x_i - mean(x)}{std\,dev(x)} \quad \textit{and} \quad \hat{y}_i = \frac{y_i - mean(y)}{std\,dev(y)}$$

- Spectral correlation does not take off the mean value:

$$\sigma_{X,Y} = \frac{\sum_{k=1}^{N}\left(\left|X(\omega_k)\right|^2\left|Y(\omega_k)\right|^2\right)}{\sum_{k=1}^{N}\left(\left|X(\omega_k)\right|^2\right)^2\sum_{k=1}^{N}\left(\left|Y(\omega_k)\right|^2\right)^2}$$

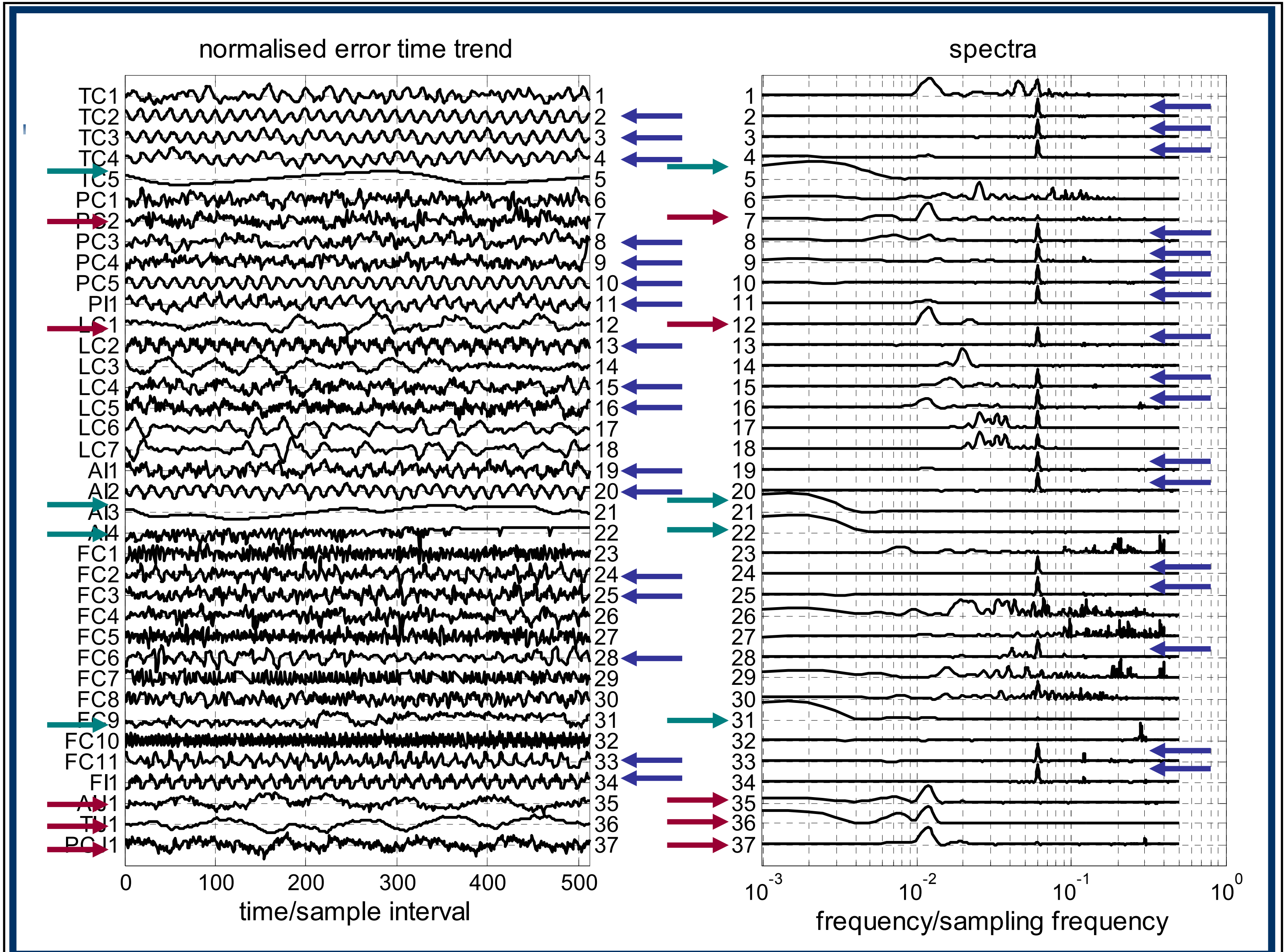
# Spectral correlation analysis

## Spectral correlation and colour map

- The example is the SE Asia data set

  Next slide shows the detected clusters;

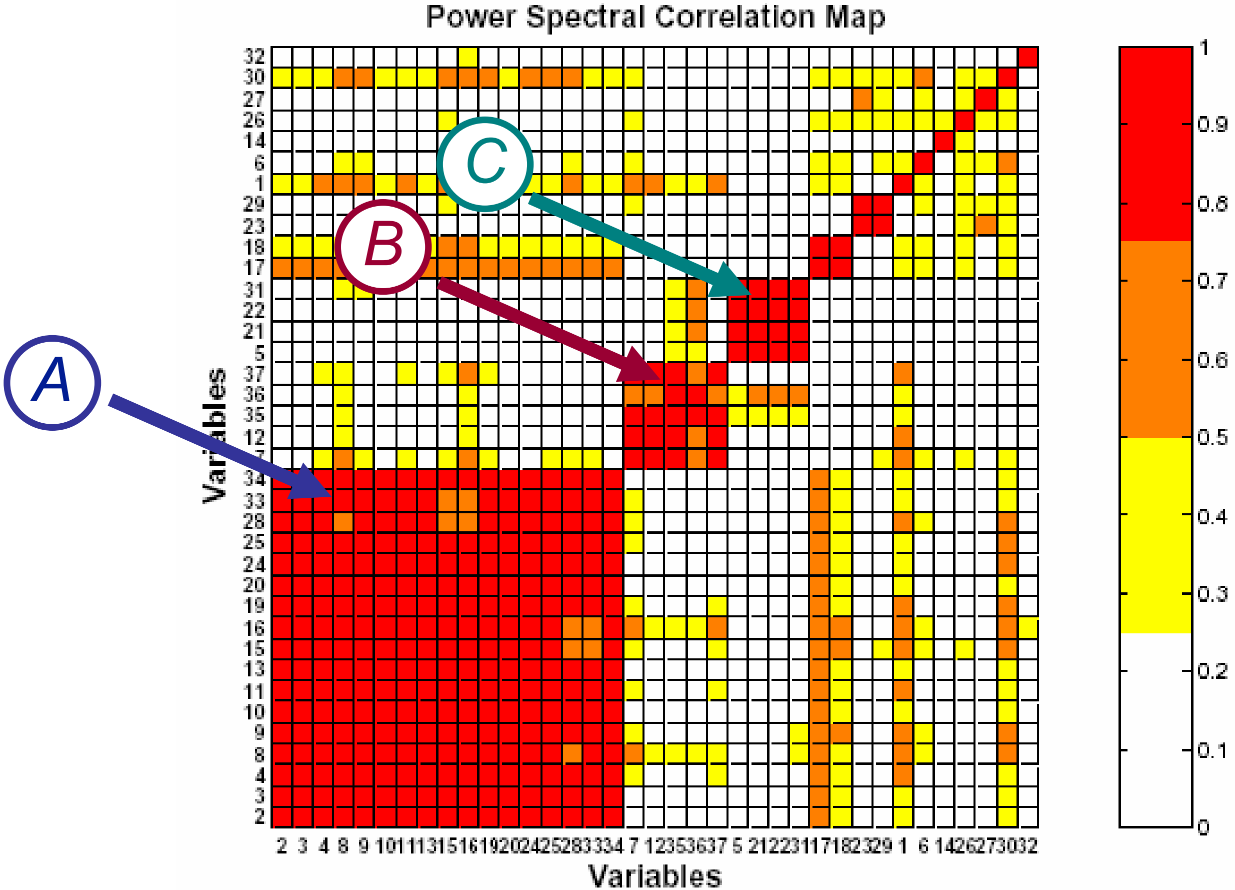
  Manual inspection is infeasible for large data sets.



normalised error time trend
spectra
TC1
TC2
TC3
TC4
TC5
PC1
PC2
PC3
PC4
PC5
PI1
LC1
LC2
LC3
LC4
LC5
LC6
LC7
AI1
AI2
AI3
AI4
FC1
FC2
FC3
FC4
FC5
FC6
FC7
FC8
FC9
FC10
FC11
FI1
AI1
TI1
PCI1
0 100 200 300 400 500
time/sample interval
$10^{-3}$ $10^{-2}$ $10^{-1}$ $10^{0}$
frequency/sampling frequency

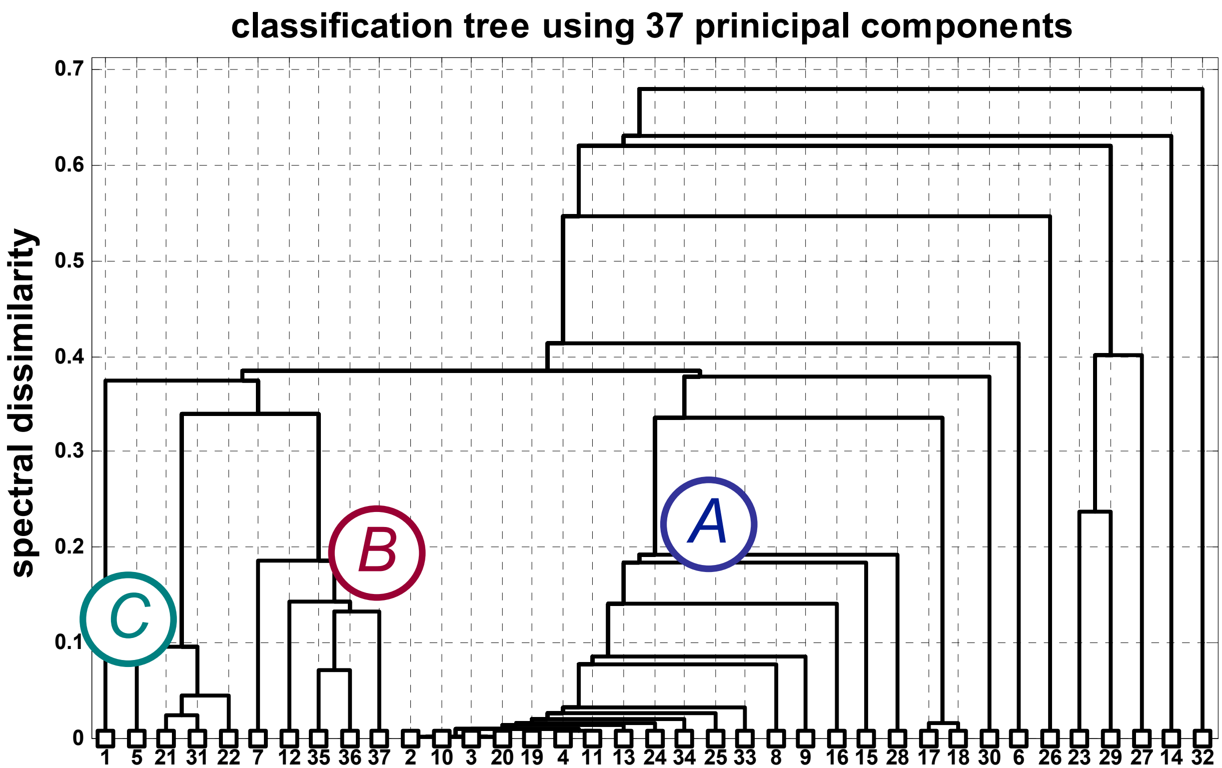
# Spectral correlation analysis

- Visualization with spectral color map



# Spectral correlation analysis

- Tree format – more complex but shows more detail



# Diagnosis of distributed disturbances: Plant-wide approaches

# Plantwide – Non-linearity tests



## Non-linearity testing

- 70% of process control problems lie with faulty valves (Ender, 1993);
- Non-linearity is most strong closest to the root cause;
- That is because process plant is low-pass, it removes harmonics and phase coherence;
- Non-linearity tests are sensitive to phase coherence;
- Two branches:

  bicoherence analysis and surrogates analysis

# Plantwide – Non-linearity tests

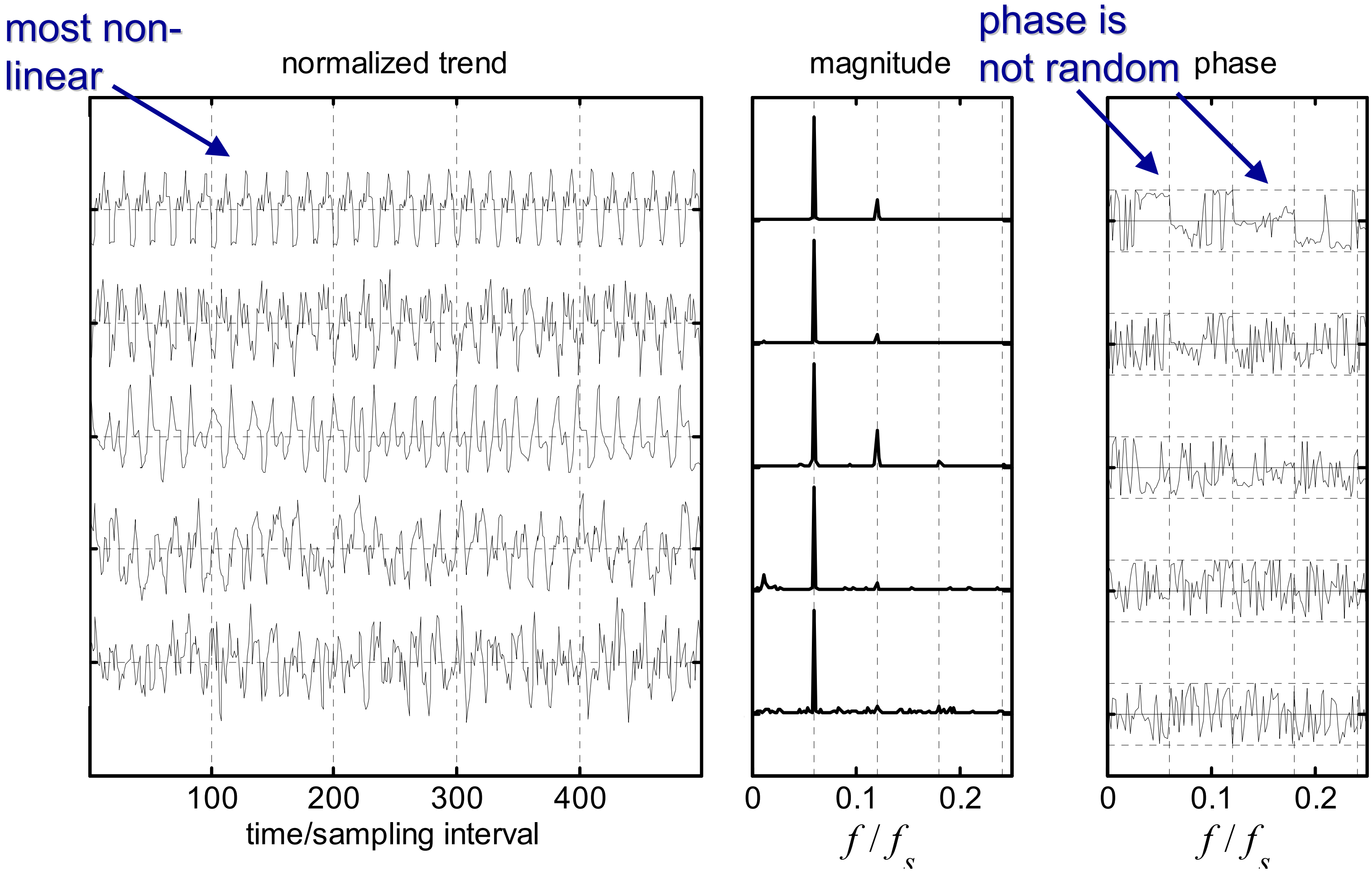
## Non-linearity testing

- Phase coherence:

  the phase in one frequency band is related to phase in other frequency bands.
- It is a characteristic of a non-linear system;
- Is $\phi_3 = \phi_1 + \phi_2$ in this signal, or is it a random phase? A non-linearity test will tell.

$$x(t) = a_1 \cos(2\pi f_1 + \phi_1) + a_2 \cos(2\pi f_2 + \phi_2) + a_3 \cos(2\pi(f_1 + f_2) + \phi_3)$$

# Plantwide – Non-linearity tests



# Diagnosis of distributed disturbances: Surrogates test

Kantz, H., & Schreiber, T., 1997, *Nonlinear time series analysis*, Cambridge University Press, Cambridge, UK.
Thornhill, N.F., Cox, J.W., and Paulonis, M., 2003, Diagnosis of plant-wide oscillation through data-driven analysis and process understanding, *Control Engineering Practice*, 11, 1481-1490.

# Plantwide – Surrogates test



## Non-linearity testing

- Non-linearity test is from Max Plank Institute at Dresden (Kantz and Schreiber, 1997);
- Could the observed time trend be the output of a linear system driven by white noise?
- Non-linearity test using surrogate data. Test the non-linear prediction error;
- Surrogates have the same spectrum as the time series under test but are phase randomized.

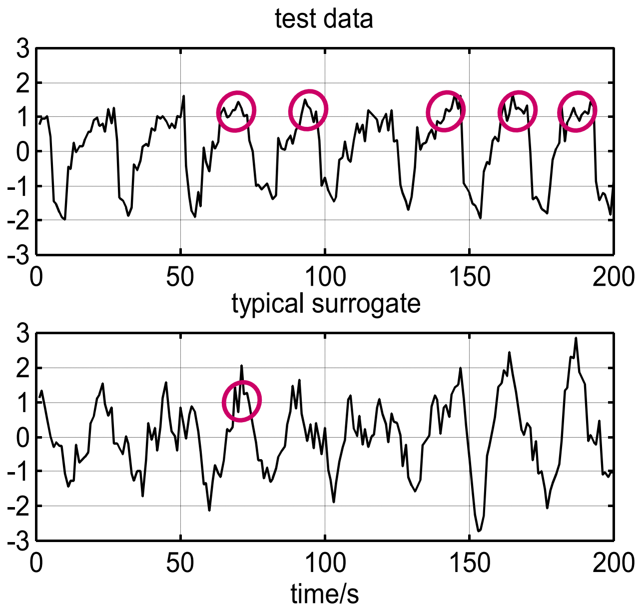
$$z = \mathrm{FFT}(\textit{test data})$$

$$z = z \, {}^{*}\exp(j\,\phi) \qquad (\textit{where } \phi \textit{ is random, } 0\text{-}2\pi)$$

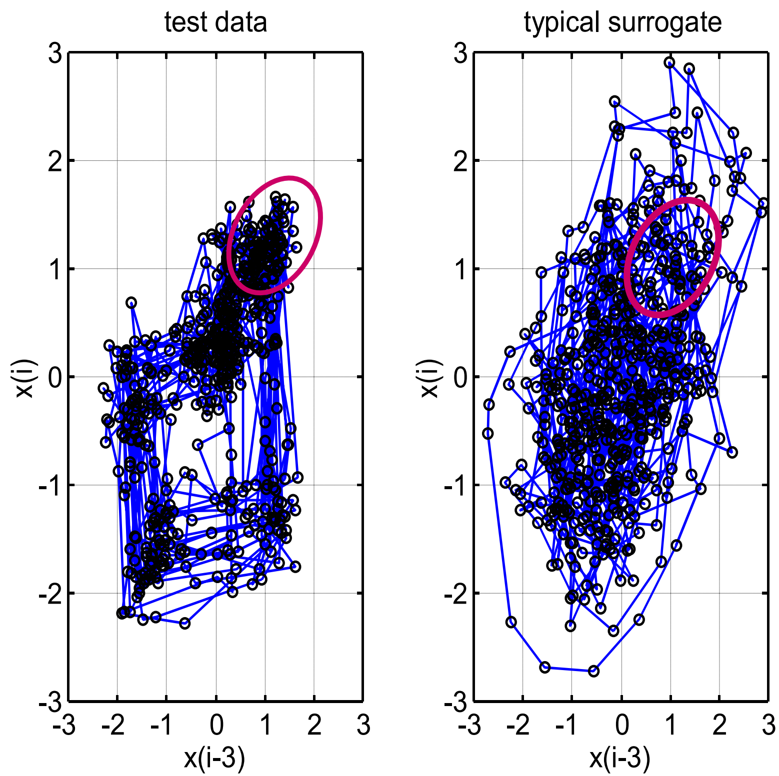
$$\textit{surrogate data} = \text{inverse FFT}(z)$$

# Plantwide – Surrogates test

## time trend




## 2-D embedded plots

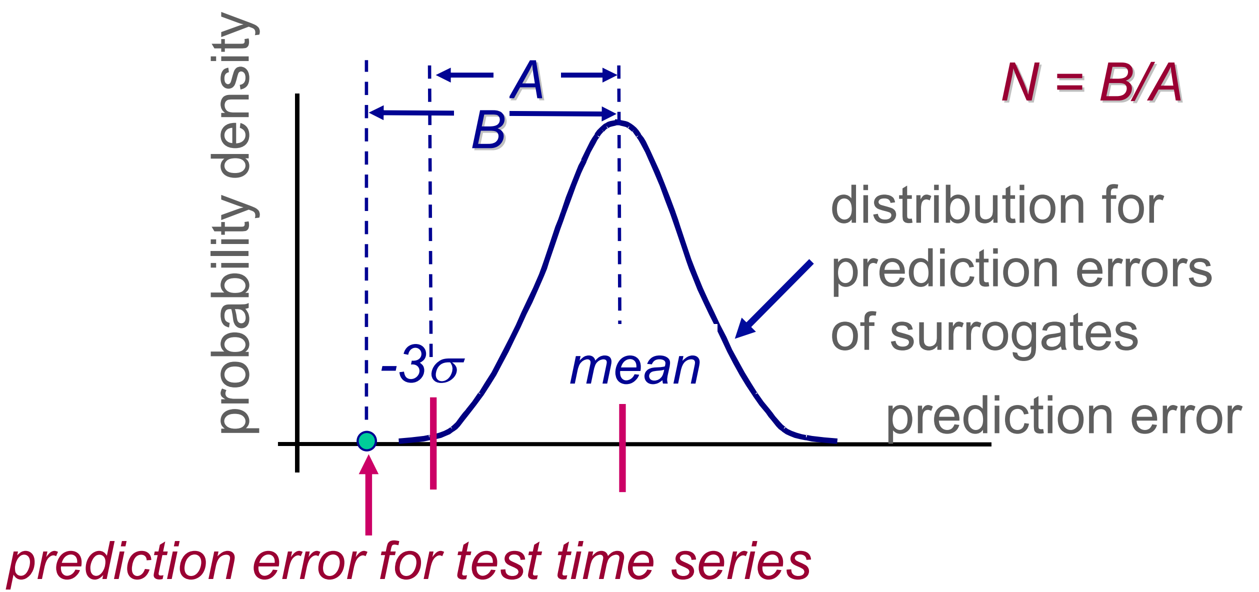



predictions are averages of near neighbours in phase plot

# Plantwide – Surrogates test

## Non-linearity testing

- *N* is the negative offset from the mean in units of 3σ;
- *N* > 1 is interpreted as non-linearity in the time series.



# Diagnosis of distributed disturbances: Bicoherence test

Choudhury, M.A.A.S., 2004, *Detection and Diagnosis of Control Loop Nonlinearities Using Higher Order Statistics*, PhD thesis, University of Alberta.

Choudhury, M.A.A.S., Shah, S.L., and Thornhill, N.F., 2004, Diagnosis of poor control loop performance using higher order statistics, *Automatica*, 40, 1719–1728.

# Plantwide – Bicoherence test

## Non-linearity testing

- Implemented by Shoukat Choudhuri, University of Alberta;

$$B(f_1,f_2) = E\left(X(f_1)\ X(f_2)\ X^*(f_1+f_2)\right)$$

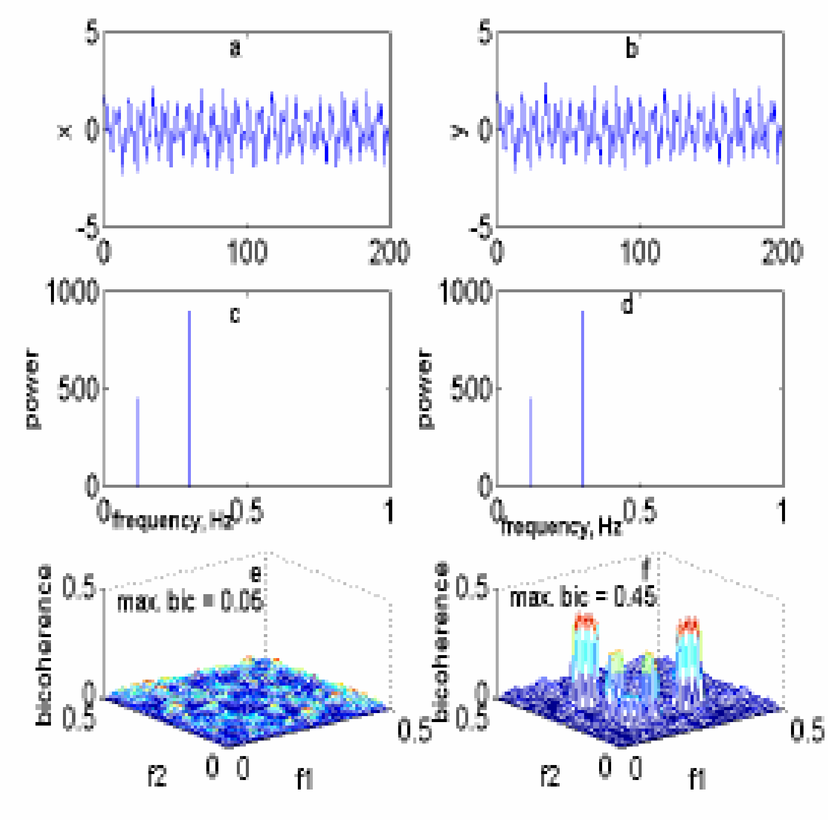
$$bic^2(f_1,f_2) = \frac{\left|B(f_1,f_2)\right|^2}{E\left(\left|X(f_1)X(f_2)\right|^2\right)E\left(\left|X(f_1+f_2)\right|^2\right)}$$

- It's a 3-D graph – horizontal axes $f_1$ and $f_2$, vertical $bic^2$;

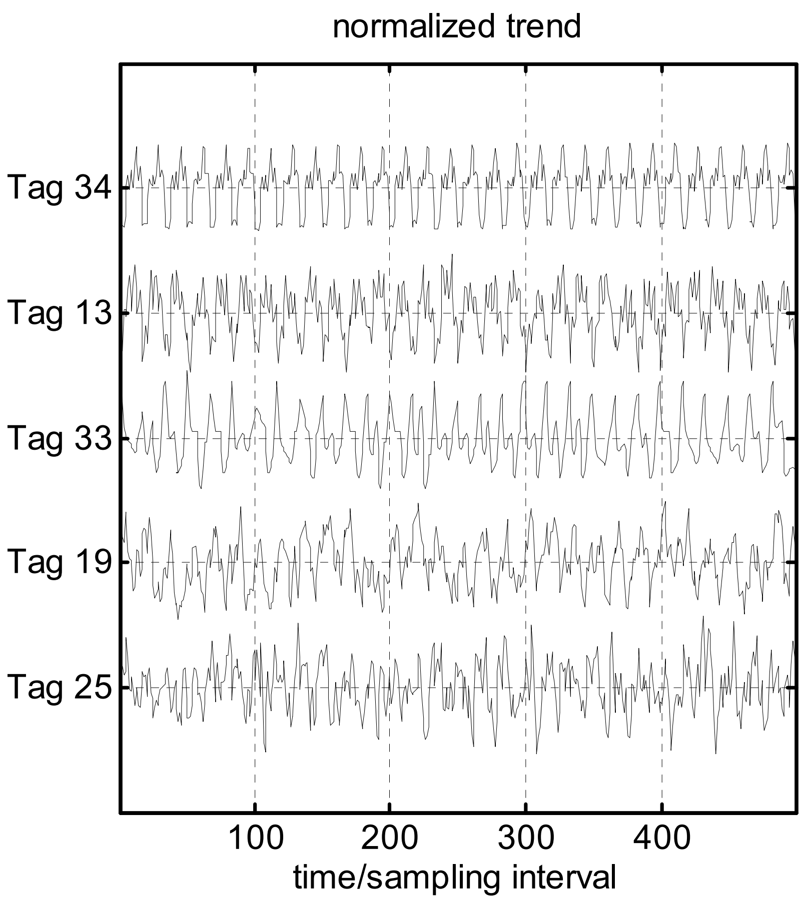
# Plantwide – Bicoherence test

## Non-linearity testing

- The left hand figure is a sum of two sine waves at ω and 2ω;
- The right hand figure is (1+ sin(ω*t*)).sin(ω*t*);
- Only the square-law signal has bicoherence;
- Figure is from Choudhury *et.al*., 2002.



# Plantwide – Both non-linearity tests

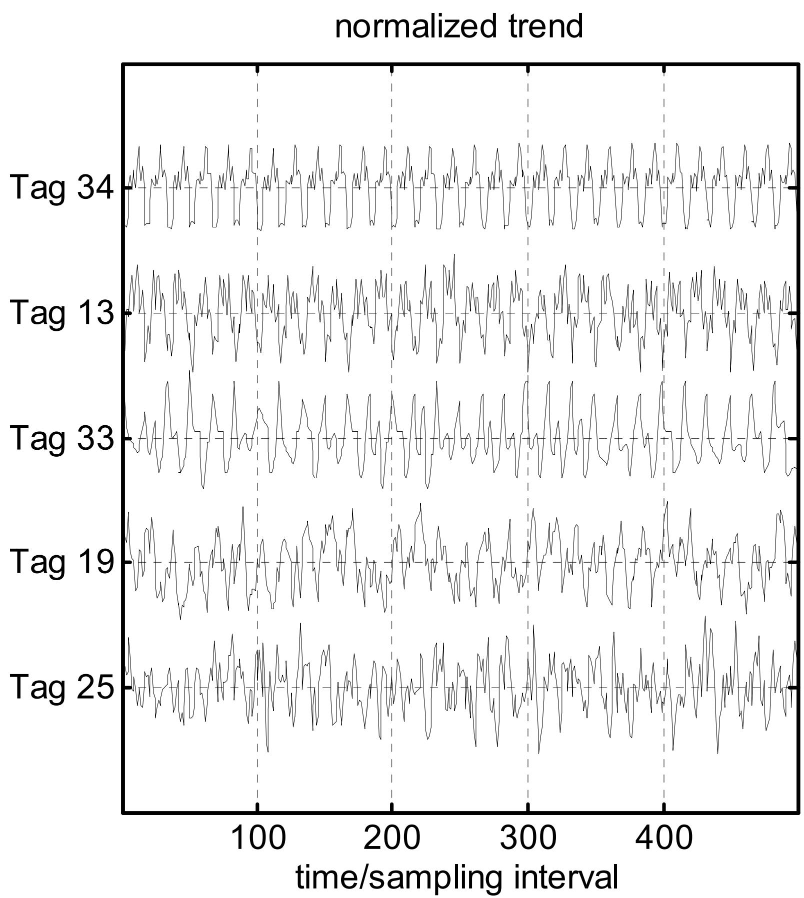


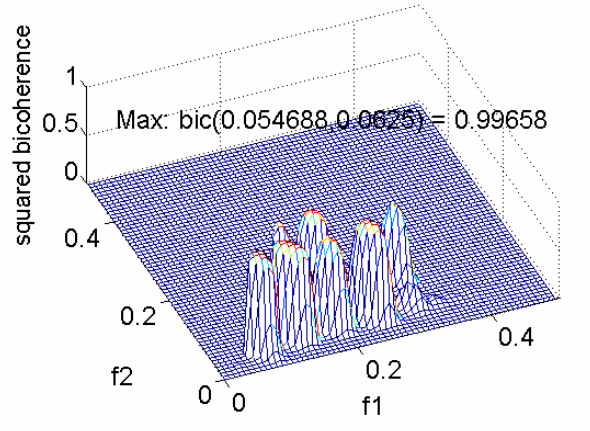

| Tag N° | max($bic^2$) | $N_{surr}$ |
|---|---|---|
| 34 | 1 | 4.9 |
| 13 | 0.9 | 2.6 |
| 33 | 1 | 2.6 |
| 19 | 0.6 | - |
| 25 | 0.3 | - |

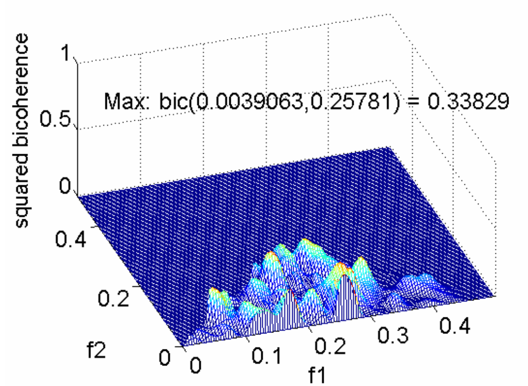
Max bicoherence and surrogates analysis give the same conclusion.

Bicoherence calculations and plots (on next slide) are by courtesy of Shoukat Choudhuri, University of Alberta.

# Plantwide – Non-linearity tests



# Diagnosis of distributed disturbances: Cause and effect analysis.

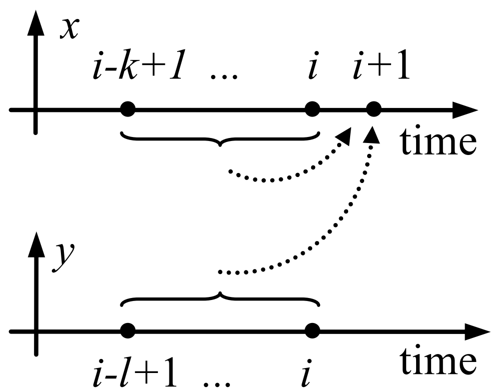
Schreiber, T., 2000, Measuring information transfer, *Physical Review Letters*, 85, 461-464.

Bauer, M., Thornhill, N.F., and Meaburn, A, 2004, Specifying the directionality of fault propagation paths using transfer entropy, *DYCOPS4 conference*, Boston, July 1-4, 2004.

# Plantwide – Cause and effect

## Entropy method

- Implementation is by Margret Bauer, UCL
- It's a method to find directionality in signals;




- Based on analysis of probability density functions (pdf)

# Plantwide – Cause and effect

## Entropy method

- Following Schreiber (2000);
- Probability of $x_{i+1}$ when **x** and **y** history are known:

$$p(x_{i+1} \mid \mathbf{x}_i^k, \mathbf{y}_i^l)$$

- Probability of $x_{i+1}$ when only **x** history is known:

$$p(x_{i+1} \mid \mathbf{x}_i^k)$$

- Normalized comparison:

$$T_{Y \to X} = \sum_{x_{i+1}} \sum_{\mathbf{x}_i^k} \sum_{\mathbf{y}_i^l} p(x_{i+1}, \mathbf{x}_i^k, \mathbf{y}_i^l) \log \frac{p(x_{i+1} \mid \mathbf{x}_i^k, \mathbf{y}_i^l)}{p(x_{i+1} \mid \mathbf{x}_i^k)}$$

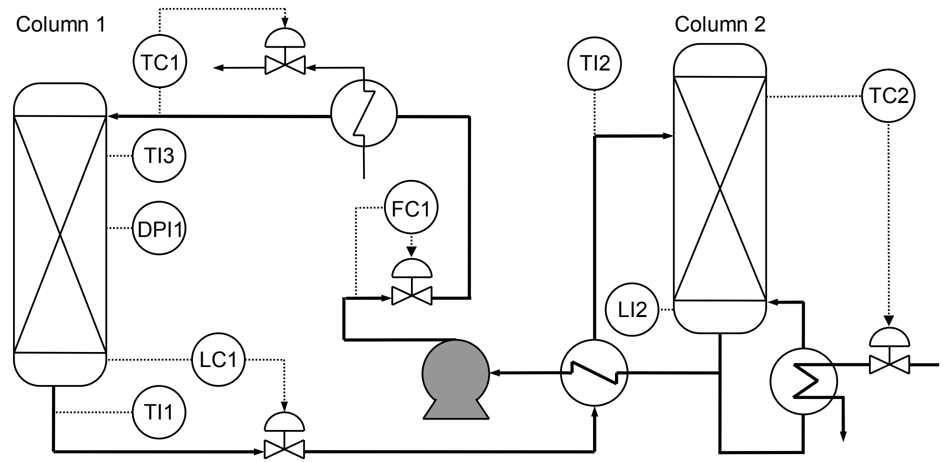
$$t_{X \to Y} = \frac{(T_{X \to Y} - T_{Y \to X})}{\min\{T_{X \to Y}, T_{Y \to X}\}}$$

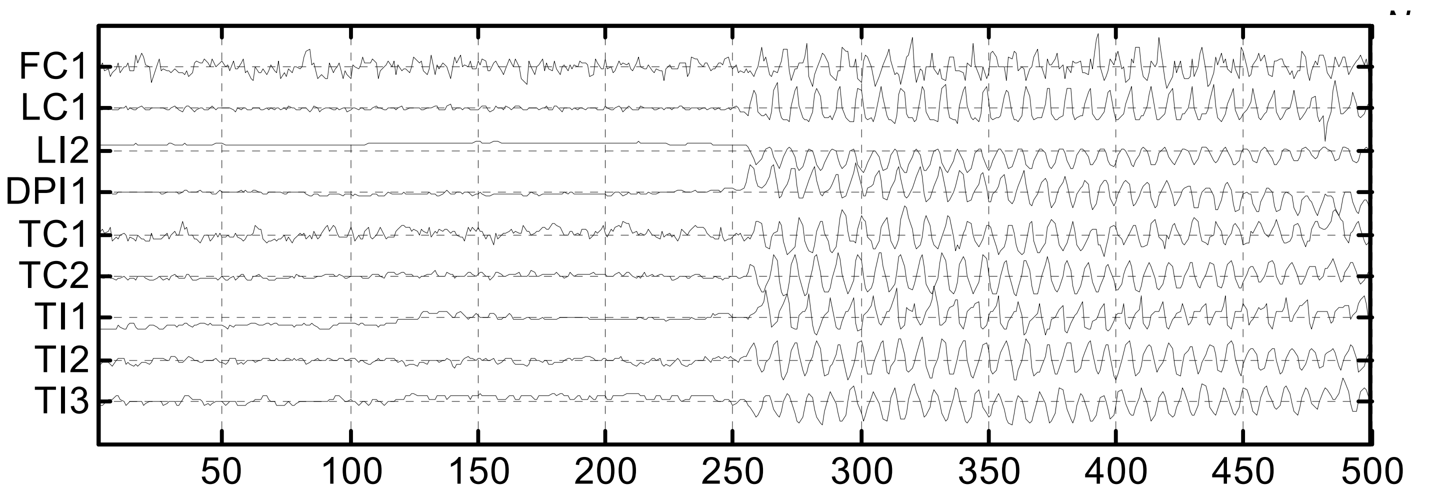
# Plantwide – Cause and effect



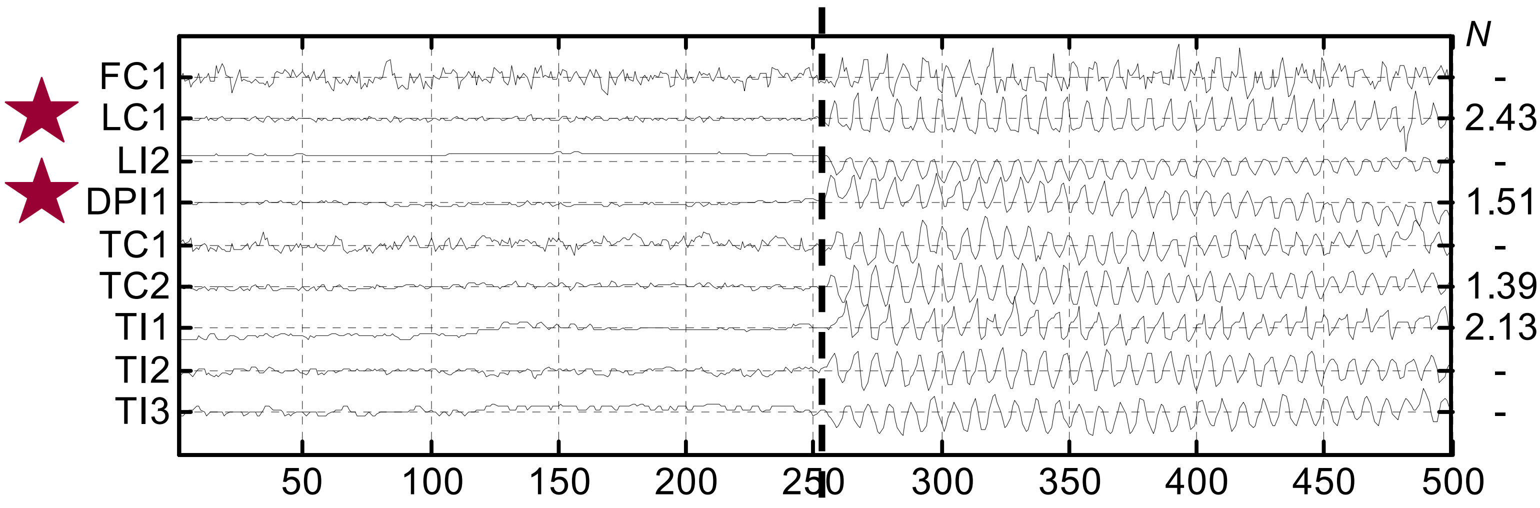
## Example

- foaming



# Plantwide – Cause and effect




$t_{DP1 \to LC1} = 0.805$

normal operation

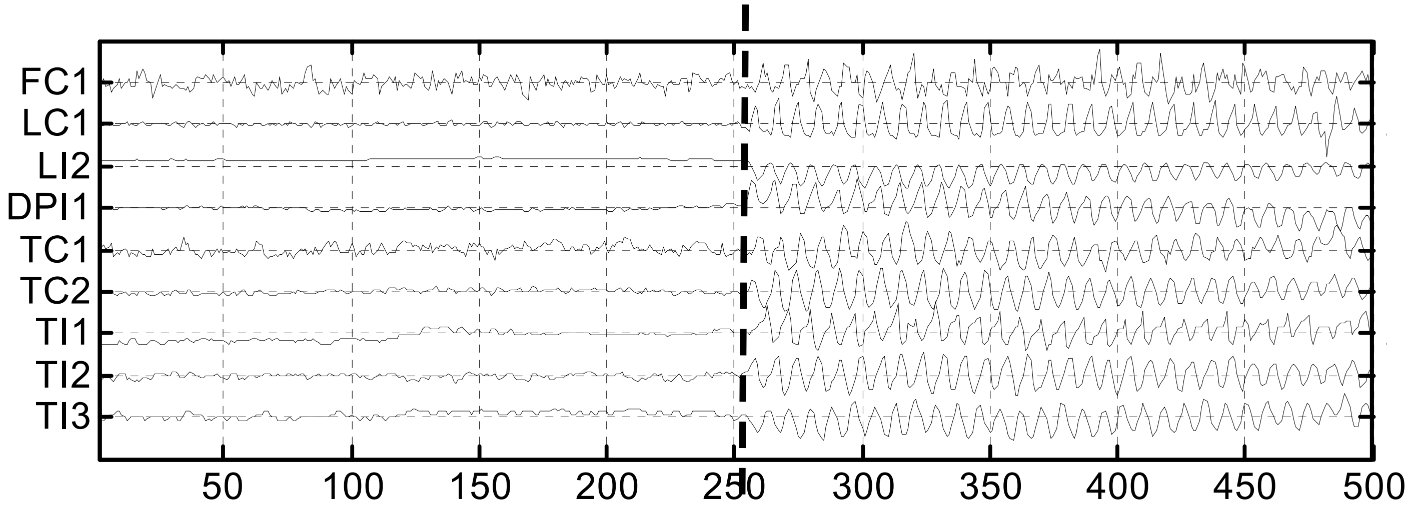
DP1 →LC1

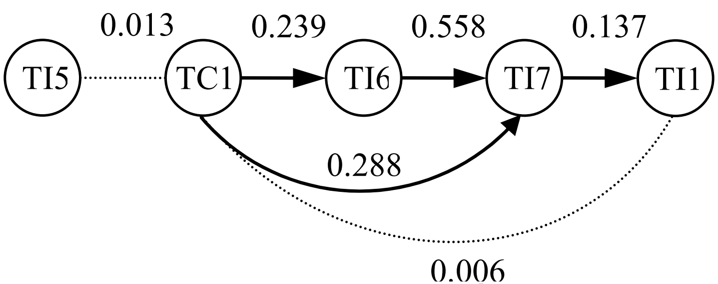
$t_{LC1 \to DP1} = 0.85$

foaming

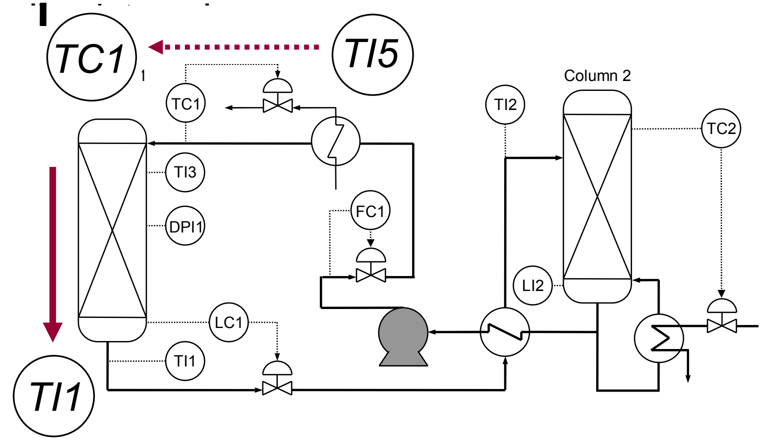
LC1 →DP1

# Plantwide – Cause and effect




normal operation



# Diagnosis of distributed disturbances: Single loop approaches

# Single loop approaches

Plant-wide analysis to isolate suspects

then

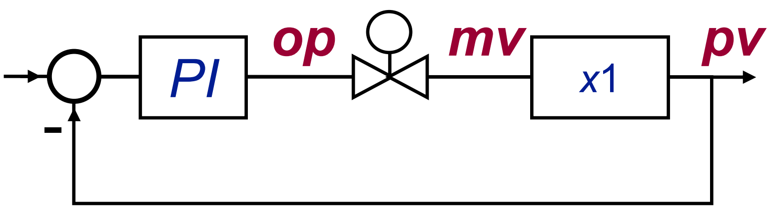
Single loop tests to confirm diagnosis, e.g.

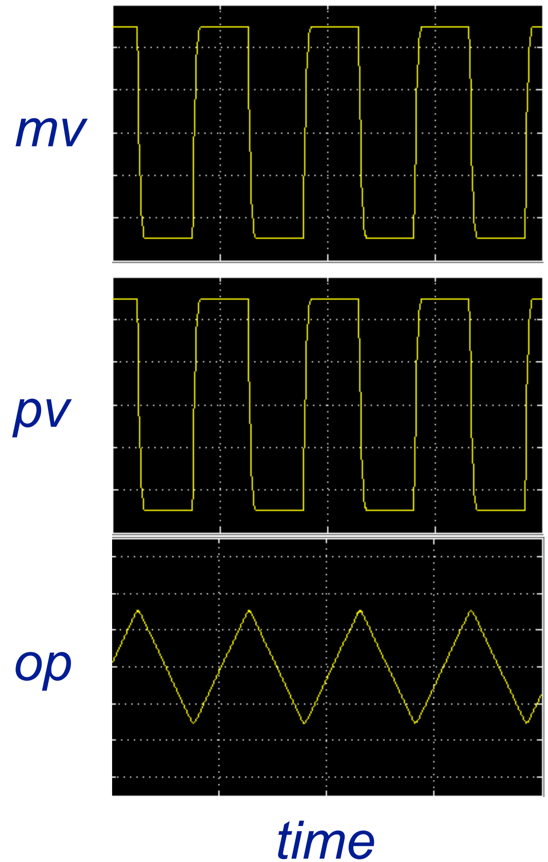
- Analysis of waveform shapes:
  - Pattern recognition
  - Even and odd cross correlation of *op* and *pv*
- Plotting of *op-mv* map;
- Changing controller gain;
- Putting loop in manual, travel tests.

# Single loop – Shape analysis

## Waveform pattern recognition

- Flow loop:
- *mv* and *pv* are square
- *op* is triangular
- *op* and *mv* are 90$^o$ out of phase

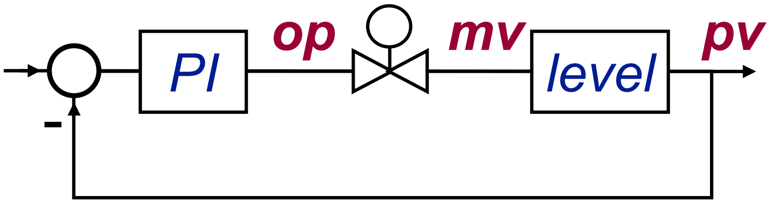


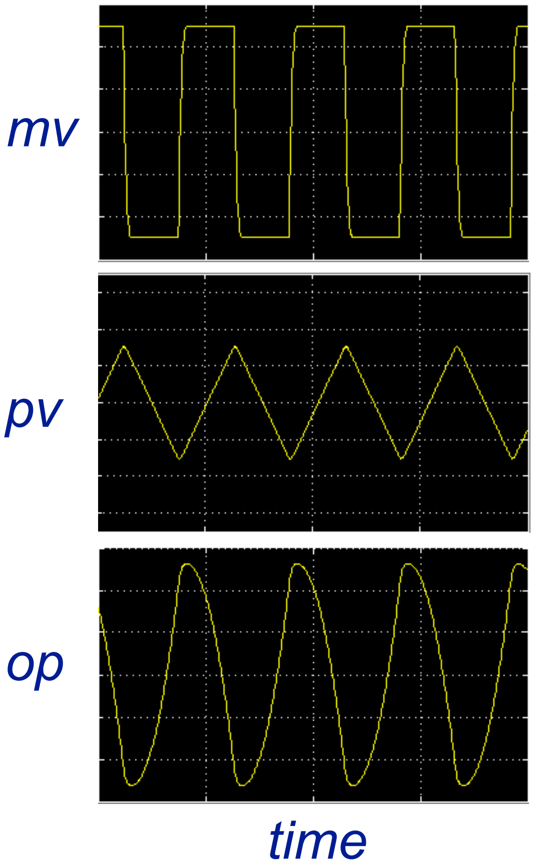



# Single loop – Shape analysis

## Waveform pattern recognition

- Integrating process dynamics:
- *mv* is square
- *pv* is triangular
- *op* has parabolic segments
- *op* and *mv* are 90° out of phase



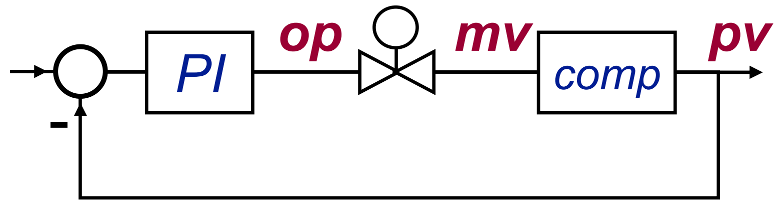
# Single loop – Shape analysis

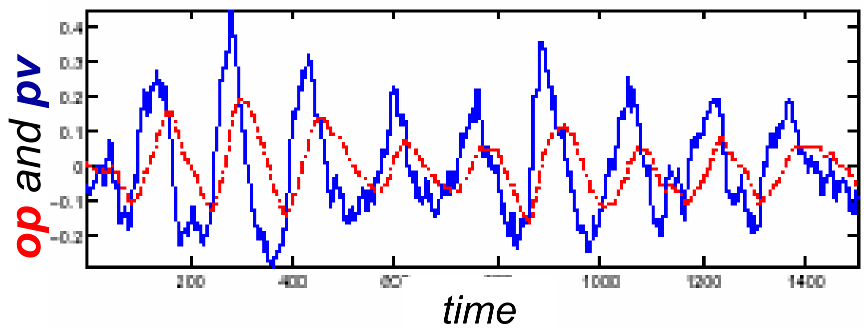
## Cross correlation

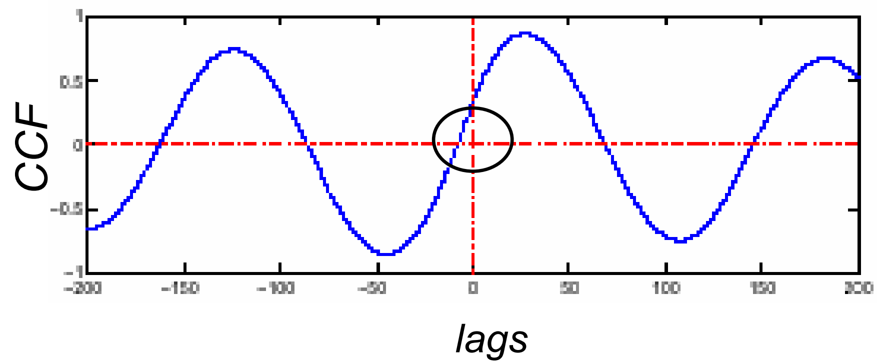
- Conceived by Alexander Horch (Figure 10.7 from his PhD thesis);
- *pv* and *op* do not have classical shapes;

  but
- process dynamics are non-integrating;
- *op* and *pv* have odd CCF;

  so stiction is present.

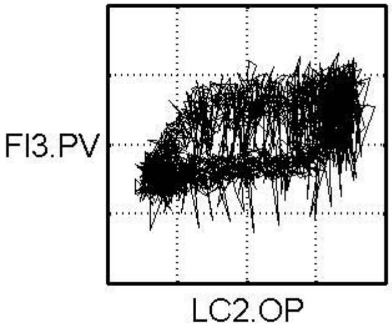


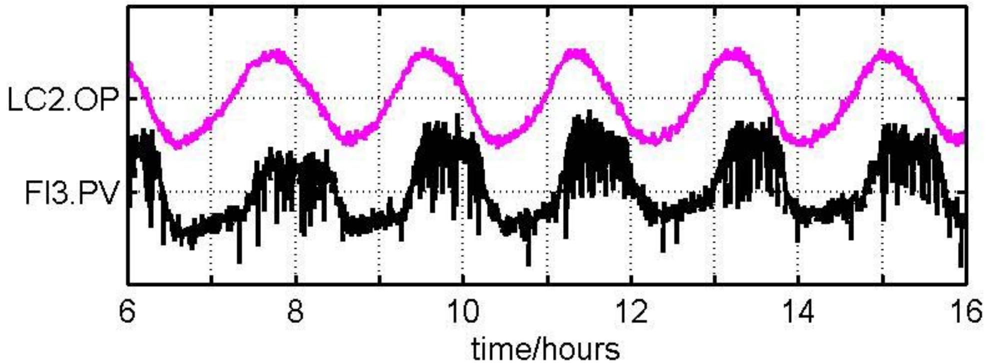



# Single loop – *op-mv* plot

- Check valve using *op - mv* plot;
- FI3 is flow through LC2 control valve;
- The LC2 valve clearly has a deadband.



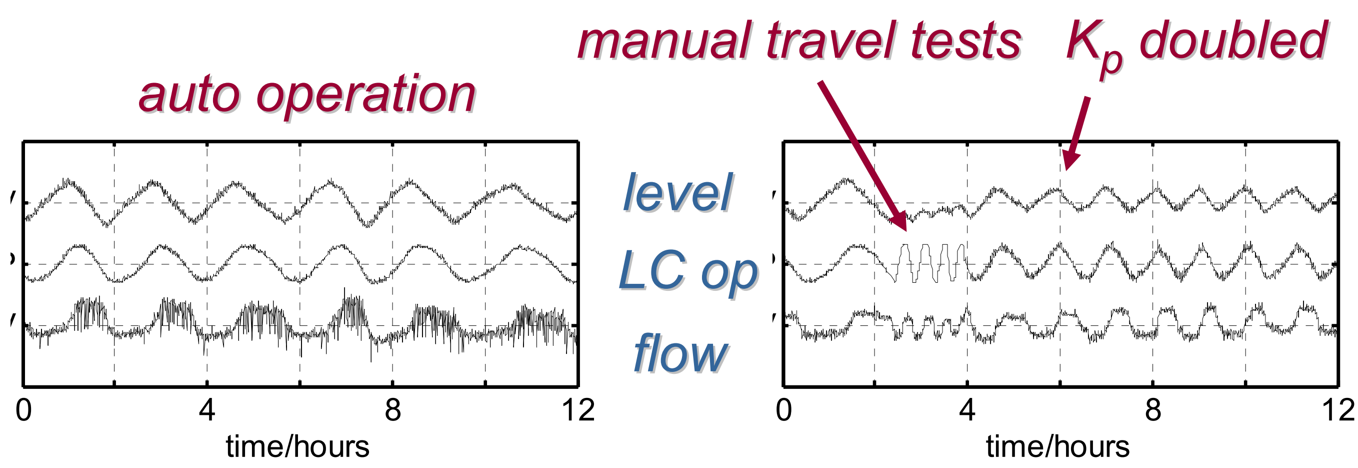
# Single loop – Plant tests



## Manual testing

- Travel tests showed deadband;
- Period and amplitude changed with controller gain;

Data from Cox and Paulonis, Eastman Chemical Company.



# Open issues in diagnosis

# Diagnosis – Open issues

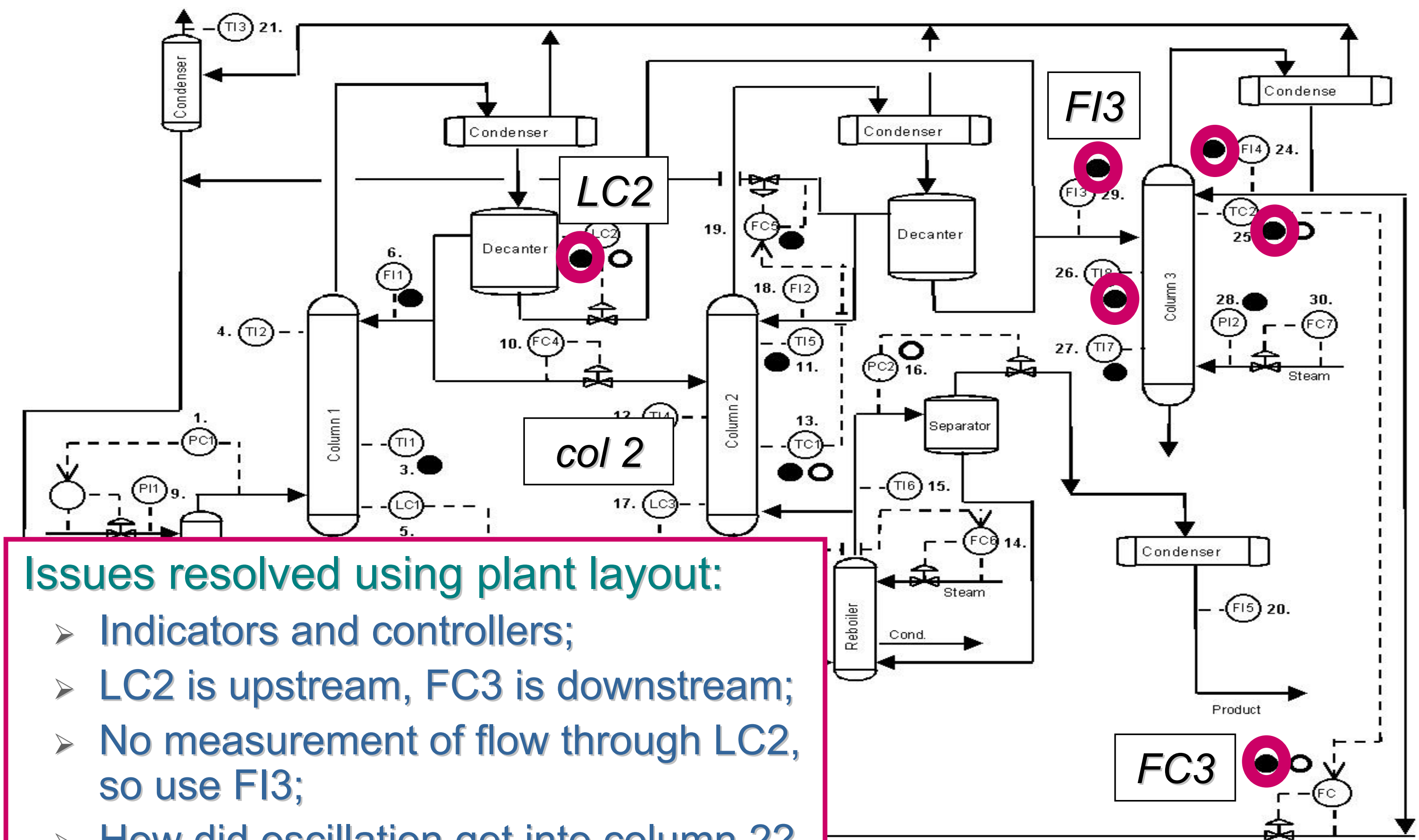
## Using plant layout

- Capture and manipulate plant layout as well as measurements.

## Diagnosis of other root causes

- Controller interaction;
- Structural disturbances e.g. recycle, snowball effect;
- Disturbances entering at plant boundaries;
- Poor tuning, hi-lo limits, range problems.

# Diagnosis – Using plant layout




## Issues resolved using plant layout:

- Indicators and controllers;
- LC2 is upstream, FC3 is downstream;
- No measurement of flow through LC2, so use FI3;
- How did oscillation get into column 2?

# Tools for users

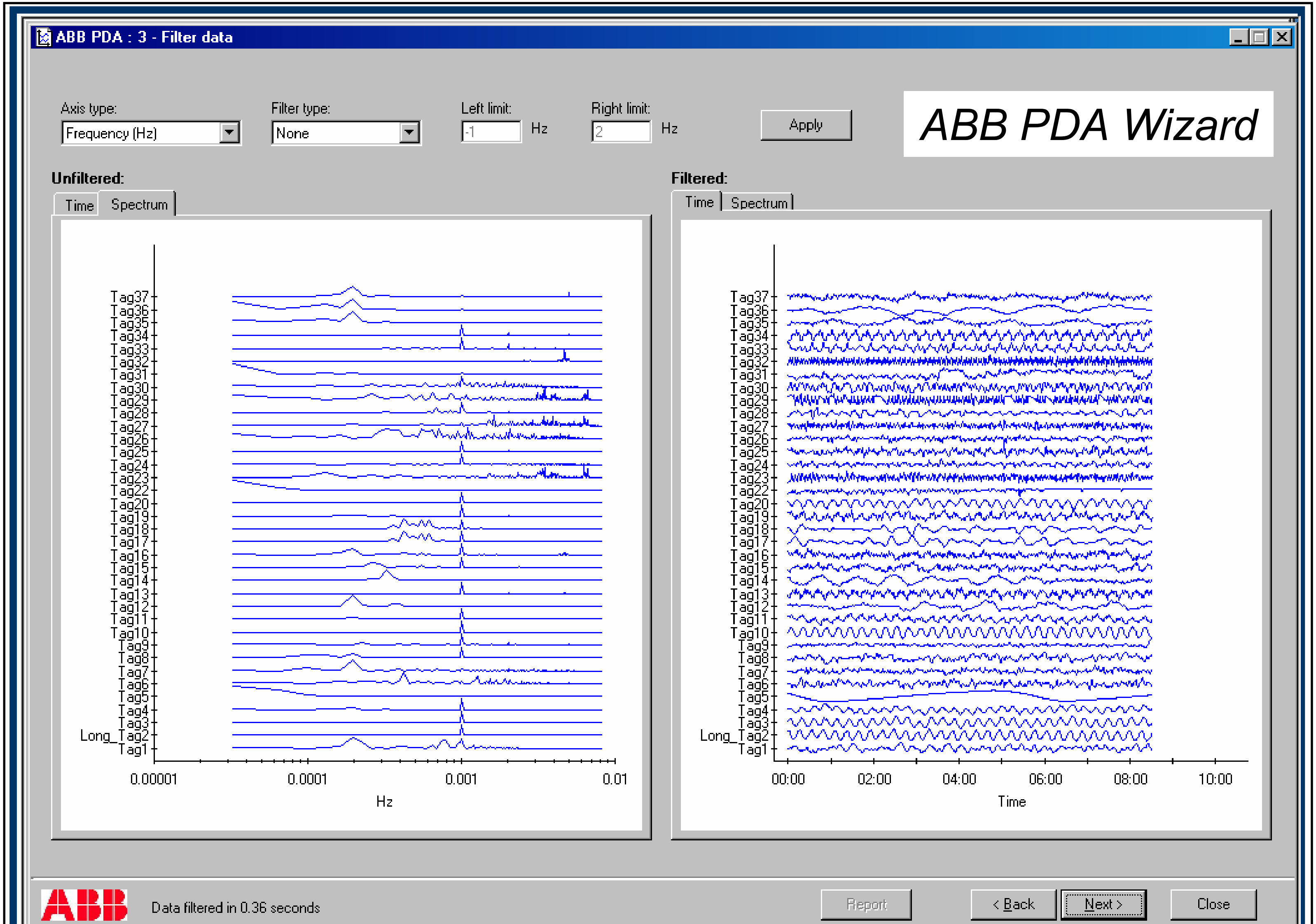
# Tools for users

## Tools using algorithms of this talk

- PDA Wizard from ABB (will be an add-on to Loop Performance Manager);
- DataProctor from University of Alberta.

## Controller performance and diagnosis

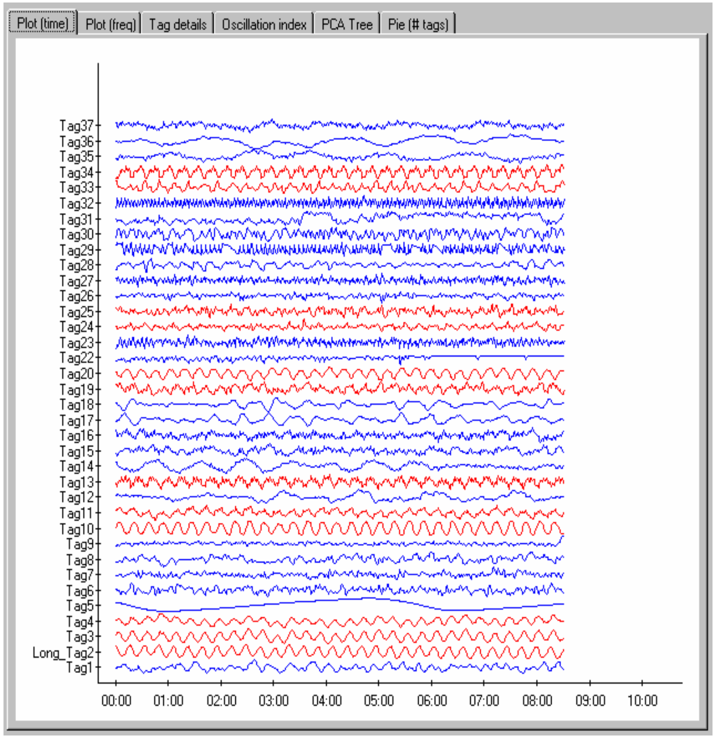
- Main vendors are reviewed shortly



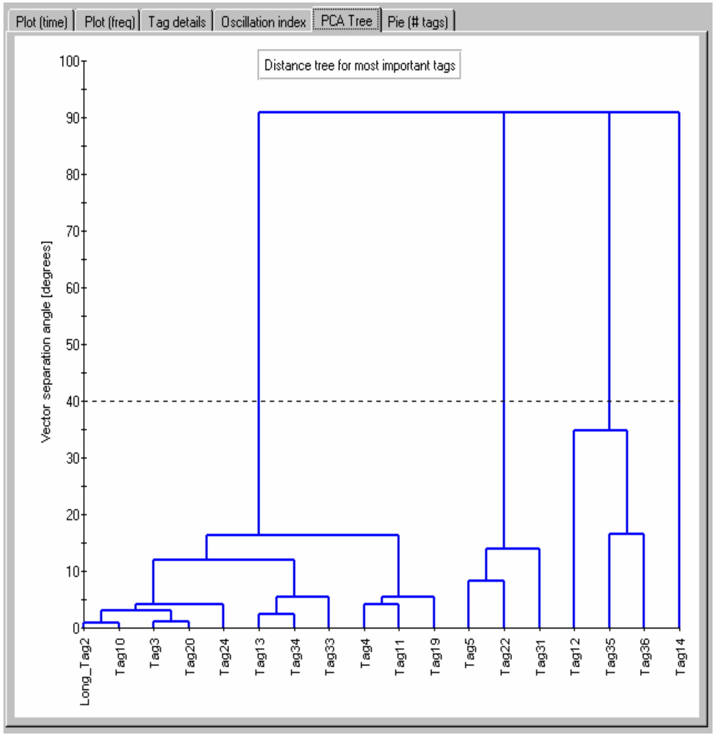

*Spectra and time trends*

# Tools for users

*ABB PDA Wizard*




*Clustering*

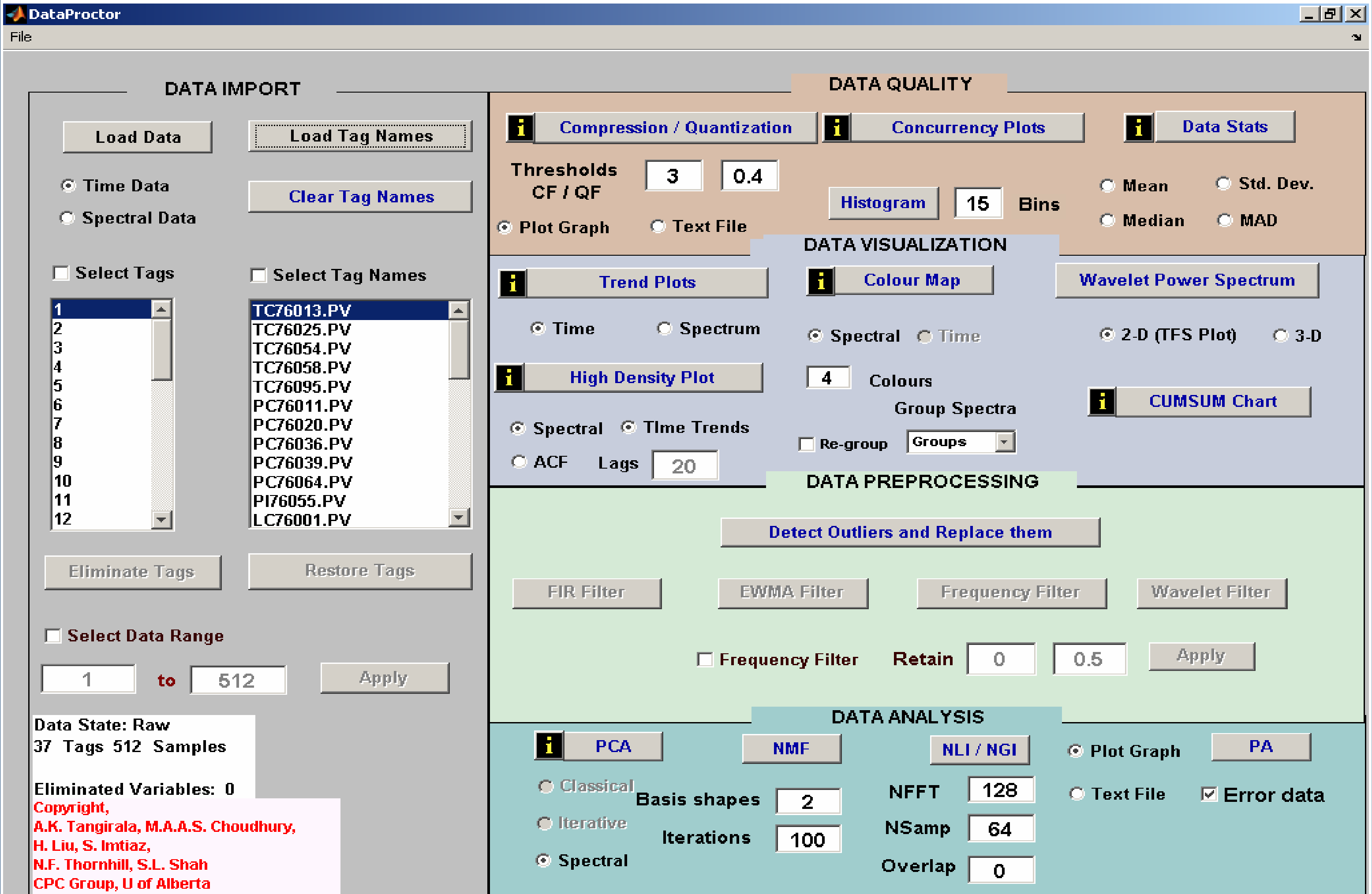



*PCA tree*

# Tools for users

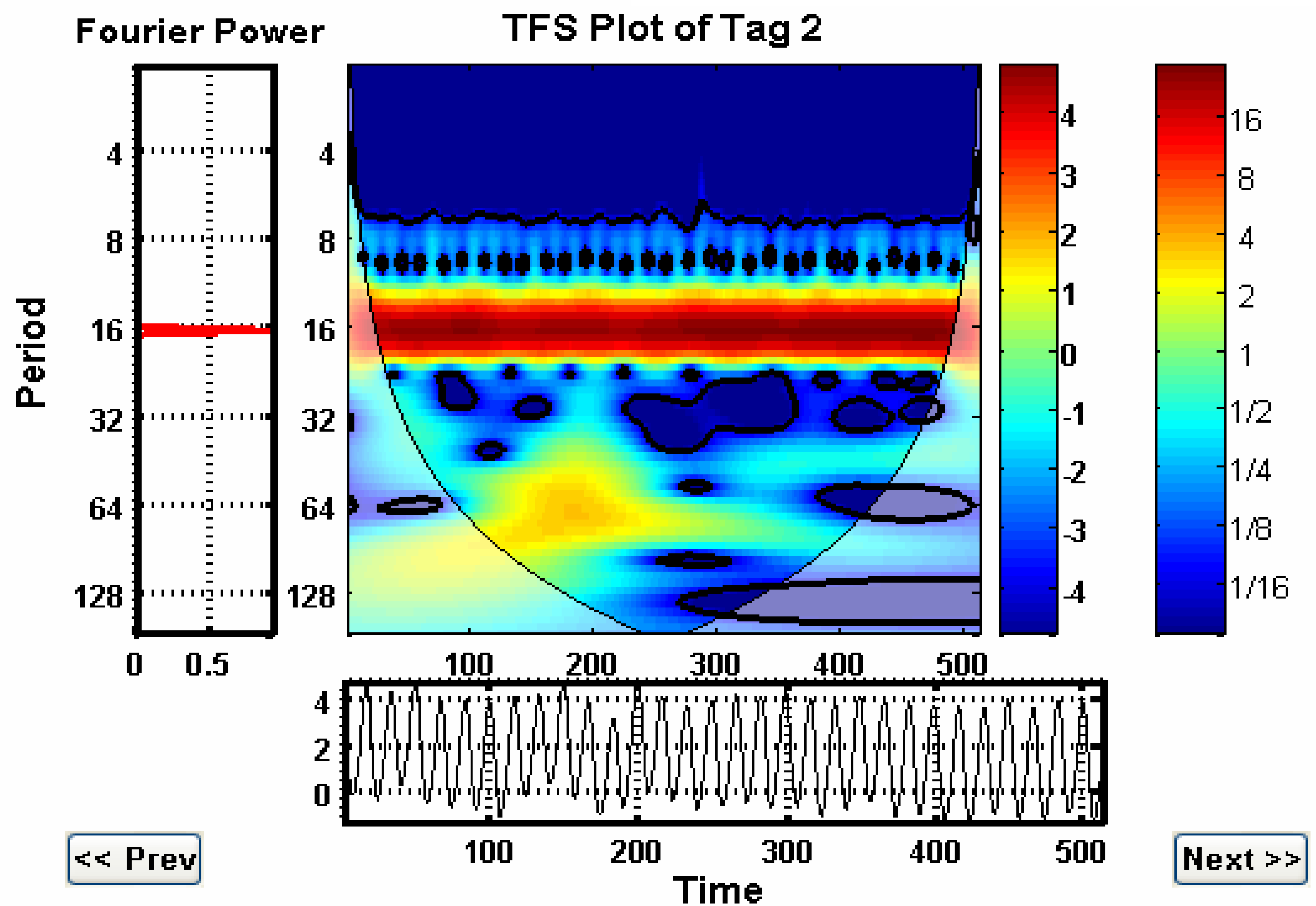
*DataProctor GUI*





# Tools for users

*DataProctor Wavelet analysis*



# Survey – Products and services



## ABB: Optimize IT Loop Performance Manager

- http://www.abb.com/ (search for Loop Performance)

## Aspentech: Aspen Watch

- http://www.aspentech.com/

## Entech/Emerson Process Management

- http://www.emersonprocess.com/entechcontrol/Services/
- http://www.emersonprocess.com/home/services/

## Honeywell: Loop Scout

- http://hpsweb.honeywell.com/Cultures/en-US/Products/AssetApplications/AssetManagement/LoopScout/default.htm

# Survey – Products and services

ISC Ltd: Probe (with U of Strathclyde)

- http://www.isc-ltd.com/software/

Matrikon: ProcessDoctor

- http://www.matrikon.com/products/processdoc/

PAS: Control Wizard

- http://www.pas.com/ControlWizard.htm

Expertune: Plant Triage

- http://www.expertune.com/planttriage.html

# Review of the presentation



## Plant-wide disturbances

- Examples

## Detection and characterization

- Multiple oscillation detection
- Clustering methods

## Isolation and diagnosis of the root cause

- Non-linearity tests
- Cause and effect analysis
- Single loop tests
- Open issues in diagnosis

## Tools for users

## Useful literature

# Useful literature



Choudhury, M.A.A.S., 2004, *Detection and Diagnosis of Control Loop Nonlinearities Using Higher Order Statistics*, PhD thesis, University of Alberta.

Choudhury M.A.A.S. , Shah, S.L., and Thornhill, N.F., 2002, Detection and diagnosis of system nonlinearities using higher order statistics, *IFAC World Congress 2002*, Barcelona, Spain.

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# Useful literature



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Paulonis, M.A., and Cox, J.W., 2003, A practical approach for large-scale controller performance assessment, diagnosis, and improvement. *Journal of Process Control*, 13, 155-168.

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# Useful literature




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Thornhill, N.F., Cox, J.W., and Paulonis, M., 2003, Diagnosis of plant-wide oscillation through data-driven analysis and process understanding, *Control Engineering Practice*, 11, 1481-149.

Thornhill, N.F., Huang, B., and Zhang, H., 2003, Detection of multiple oscillations in control loops, *Journal of Process Control*, 13, 91-100.

Xia, C., 2003, *Control Loop Measurement Based Isolation of Faults and Disturbances in Process Plants*, PhD Thesis, University of Glasgow, 2003.

Xia, C., and Howell, J., 2003, Loop status monitoring and fault localisation. *Journal of Process Control*, 13, 679-691.

Xia, C., Howell, J., and Thornhill, N.F., 2005, Detecting and isolating multiple plant-wide oscillations via spectral independent component analysis, *Automatica, accepted for publication*.

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