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).
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

![Graph showing time and variables over 48 hours with specific variables labeled on the x-axis such as PC1, FC3, TC1, TI1, TI2, LC1, FI1, FC1, FC2, PI1, FC4, TI5, TI4, TC1, FC6, TI6, PC2, LC3, FI2, FC5, FI5, TI3, LC2, FC8, FI4, TC2, TI8, TI7, PI2, FI3, FC7. The x-axis is labeled as time/hours and ranges from 0 to 48. There is a red star indicating a specific point.]
Distributed disturbances

oscillating measurement
Example (SE Asia data)

- Valve problem
Distributed disturbances

Example (BP)

- foaming
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

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 .....
Plant-wide oscillation detection

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

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

where \( y \) is mean-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 ($\sigma_{\Delta T_p}$) 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 $O.I > 1$ is a 3-sigma rejection of the null hypothesis of random zero crossings.
Oscillation detection

- Normalised time trend
- Autocovariance functions
- Zero crossings

<table>
<thead>
<tr>
<th>O.I.</th>
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<tbody>
<tr>
<td>0.6</td>
</tr>
<tr>
<td>1.1</td>
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<tr>
<td>2.4</td>
</tr>
<tr>
<td>0.2</td>
</tr>
<tr>
<td>4.2</td>
</tr>
<tr>
<td>0.1</td>
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<td>3.4</td>
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<td>0.9</td>
</tr>
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<td>0.2</td>
</tr>
<tr>
<td>0.9</td>
</tr>
<tr>
<td>0.3</td>
</tr>
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</table>
# Oscillation detection

## Oscillation results

<table>
<thead>
<tr>
<th>Plant-wide analysis</th>
<th>tags involved</th>
</tr>
</thead>
<tbody>
<tr>
<td>ave_period</td>
<td></td>
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<tr>
<td>17.67</td>
<td>16 15</td>
</tr>
<tr>
<td>347.9</td>
<td>25 5 23 7 22 8 26 19 13 12</td>
</tr>
<tr>
<td>1384</td>
<td>2</td>
</tr>
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</table>
Detection of distributed disturbances: Spectral principal component analysis

Spectral PCA

normalised time trend

spectra

<table>
<thead>
<tr>
<th>time/sample interval</th>
<th>frequency/sampling frequency</th>
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</thead>
<tbody>
<tr>
<td>0</td>
<td>$10^{-4}$</td>
</tr>
<tr>
<td>1</td>
<td>$10^{-3}$</td>
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<tr>
<td>2</td>
<td>$10^{-2}$</td>
</tr>
<tr>
<td>3</td>
<td>$10^{-1}$</td>
</tr>
<tr>
<td>4</td>
<td>$10^0$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

...
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.

\( \mathbf{X} \) is matrix of spectra, 30 rows and 4196 columns.

- 4196 frequencies
- 30 spectra, one for each tag

Method

- Decompose \( \mathbf{X} \) as a sum over basis functions \( \mathbf{X} = \mathbf{T} \mathbf{P}^\prime \)
- The \( \mathbf{T} \) vectors are the scores. The basis functions are the rows of the loadings matrix \( \mathbf{P}^\prime \)
Spectral PCA

e.g. For a 3 - PC model:

\[ X = \begin{pmatrix} t_{1,1} \\ \vdots \\ t_{m,1} \end{pmatrix} p_1^\prime + \begin{pmatrix} t_{1,2} \\ \vdots \\ t_{m,2} \end{pmatrix} p_2^\prime + \begin{pmatrix} t_{1,3} \\ \vdots \\ t_{m,3} \end{pmatrix} p_3^\prime + E \]

- 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 \( p^\prime \)-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:

normalised spectra

PCA score plot

origin \{0,0,0\} is here

frequency/sampling frequency
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

<table>
<thead>
<tr>
<th>N</th>
<th>Var %</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>47.12</td>
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<tr>
<td>2</td>
<td>75.29</td>
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<tr>
<td>3</td>
<td>98.51</td>
</tr>
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<td>4</td>
<td>98.99</td>
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<tr>
<td>5</td>
<td>99.33</td>
</tr>
<tr>
<td>6</td>
<td>99.58</td>
</tr>
<tr>
<td>7</td>
<td>99.71</td>
</tr>
<tr>
<td>8</td>
<td>99.78</td>
</tr>
<tr>
<td>9</td>
<td>99.82</td>
</tr>
<tr>
<td>10</td>
<td>99.85</td>
</tr>
<tr>
<td>11</td>
<td>99.88</td>
</tr>
<tr>
<td>12</td>
<td>99.90</td>
</tr>
</tbody>
</table>

3 PCs (98.5%)

30 PCs (100%)
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


Reconstruction of spectra using $X = T \times P'$

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

Linear combinations can separate the peaks

loading plot  linear combinations of loadings

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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

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:

\[
\sigma_{x,y} = \frac{1}{N} \sum_{i=1}^{N} (\hat{x}_i \hat{y}_i)
\]

where \( \hat{x}_i = \frac{x_i - \text{mean}(x)}{\text{std dev}(x)} \) and \( \hat{y}_i = \frac{y_i - \text{mean}(y)}{\text{std dev}(y)} \)

- Spectral correlation does not take off the mean value:

\[
\sigma_{X,Y} = \frac{\sum_{k=1}^{N} \left| X(\omega_k) \right|^2 \left| Y(\omega_k) \right|^2}{\sum_{k=1}^{N} \left| X(\omega_k) \right|^2 \sum_{k=1}^{N} \left| Y(\omega_k) \right|^2}
\]
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.
Spectral correlation analysis

normalised error time trend

time/sample interval

spectra

frequency/sampling frequency
Spectral correlation analysis

- Visualization with spectral color map

![Power Spectral Correlation Map]
Spectral correlation analysis

- Tree format – more complex but shows more detail
Diagnosis of distributed disturbances: Plant-wide approaches
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
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

Most non-linear

Normalized trend

Phase is not random

Magnitude

Phase

100 200 300 400
Time/sampling interval

0 0.1 0.2
f/f_s

0 0.1 0.2
f/f_s

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Diagnosis of distributed disturbances:
Surrogates test

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.

\[ z = \text{FFT}(\text{test data}) \]
\[ z = z \ast \exp(j\phi) \quad (\text{where } \phi \text{ is random, } 0-2\pi) \]

surrogate data = inverse FFT(z)
Plantwide – Surrogates test

predictions are averages of near neighbours in phase plot
Non-linearity testing

- $N$ is the negative offset from the mean in units of $3\sigma$;
- $N > 1$ is interpreted as non-linearity in the time series.
Diagnosis of distributed disturbances: Bicoherence test

Plantwide – Bicoherence test

Non-linearity testing

- Implemented by Shoukat Choudhuri, University of Alberta;

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

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

- It's a 3-D graph – horizontal axes \( f_1 \) and \( f_2 \), vertical \( \text{bic}^2 \);
Non-linearity testing

- The left hand figure is a sum of two sine waves at $\omega$ and $2\omega$;
- The right hand figure is $(1 + \sin(\omega t)).\sin(\omega t)$;
- Only the square-law signal has bicoherence;
- Figure is from Choudhury et al., 2002.
Plantwide – Both non-linearity tests

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

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

normalized trend

Tag 34
Tag 13
Tag 33
Tag 19
Tag 25

time/sampling interval

squared coherence

Max: bic(0.054688, 0.0826) = 0.99658

squared coherence

Max: bic(0.0039063, 0.25781) = 0.33829
Diagnosis of distributed disturbances: Cause and effect analysis.


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:
  $$p(x_{i+1} | x^k_i, y^l_i)$$
- Probability of $x_{i+1}$ when only $x$ history is known:
  $$p(x_{i+1} | x^k_i)$$
- Normalized comparison:
  $$T_{Y \rightarrow X} = \sum_{x_{i+1}} \sum_{x^k_i} \sum_{y^l_i} p(x_{i+1}, x^k_i, y^l_i) \log \frac{p(x_{i+1} | x^k_i, y^l_i)}{p(x_{i+1} | x^k_i)}$$
  $$t_{X \rightarrow Y} = \frac{(T_{X \rightarrow Y} - T_{Y \rightarrow X})}{\min \{T_{X \rightarrow Y}, T_{Y \rightarrow X}\}}$$
Plantwide – Cause and effect

Example

- foaming
Plantwide – Cause and effect

\[ t_{DP1 \rightarrow LC1} = 0.805 \]
normal operation
\[ t_{LC1 \rightarrow DP1} = 0.85 \]
foaming
\[ DP1 \rightarrow LC1 \]
\[ LC1 \rightarrow DP1 \]
Plantwide – Cause and effect

Normal operation:

- FC1
- LC1
- LI2
- DPI1
- TC1
- TC2
- TI1
- TI2
- TI3

TC1

TI5

0.013 0.239 0.558 0.137

0.288 0.006

TI1

TI6

TI7

TI1

TI2

TI3

TI4

TC2

DPI1

LI2

FC1

LC1

Index
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° out of phase

![Flow loop diagram](image)
Single loop – Shape analysis

Waveform pattern recognition

- Integrating process dynamics:
  - $mv$ is square
  - $pv$ is triangular
  - $op$ has parabolic segments
  - $op$ and $mv$ are $90^\circ$ out of phase

\[
\begin{align*}
\text{MV} &\quad \text{PV} \\
\text{PI} &\quad \text{LV} \\
\text{OP} &\quad \text{TIME}
\end{align*}
\]
Cross correlation

- Conceived by Alexander Horch (Figure 10.7 from his PhD thesis);
- $pv$ and $op$ do not have classical shapes;
- process dynamics are non-integrating;
- $op$ and $pv$ have odd CCF;
- so stiction is present.
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.

![Graph showing auto operation and manual travel tests with Kp doubled]
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.
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

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Tools for users

DataProctor GUI

DATA IMPORT

Load Data
Load Tag Names

Clear Tag Names

Time Data
Spectral Data

Select Tags
Select Tag Names

DATA QUALITY

Compression / Quantization
Concurrence Plots
Data Stats

Thresholds
CF / QF

3 0.4

Histrogram

15 Bins

Plots Graph
Text File

Mean
Std. Dev.

Median
MAD

DATA VISUALIZATION

Trend Plots
Colour Map
Wavelet Power Spectrum

Spectral
Time

Spectral
Time Trends

Group Spectra

Colour

Wavelet
Power
Spectrum

DATA PREPROCESSING

Detect Outliers and Replace them

FIR Filter
EWMA Filter
Frequency Filter
Wavelet Filter

DATA ANALYSIS

PCA
NMF

NL / NGI

Basis shapes
Iterations

2

NFFT
NSamp
Overlap

128
64
0

Detect
Outliers
and
Replace
them

Frequency
Filter

Retain
0

0.5

Apply

Error data

Plot Graph
Text File

Error data

Plot Graph
Text File
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)

Matrikon: ProcessDoctor

PAS: Control Wizard
- http://www.pas.com/ControlWizard.htm

Expertune: Plant Triage
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


Useful literature


