1

Detection and diagnosis of plant-wide disturbances

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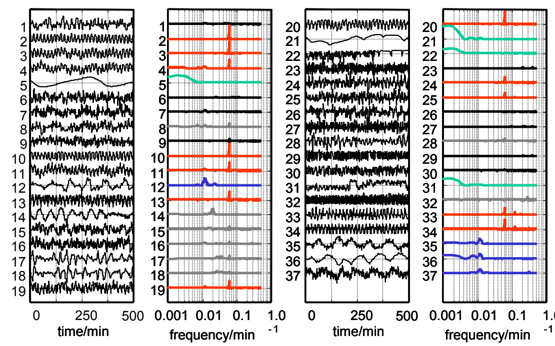
Layout of the presentation 2

- Plant-wide disturbances
  - Context of the work presented;
  - Example;
  - Principal components analysis using power spectra.
- Diagnosis of plant wide disturbances

Plant-wide disturbances - context 3

- Automated detection and diagnosis of plant wide disturbances is a research topic.
- Approaches include:
  - Feedforward/cross correlation (Stanfelj et.al., 1993; Desborough and Harris, 1993);
  - Capture of cause and effect in a model using signed directional graphs (Chen and Howell, 2001);
  - An index involving controller output (Xia and Howell, 2001a,b);
  - Signatures for nonlinearity
- Work presented here is current research
  - Presented at conferences (2000, 2001), journal papers submitted;

Plant-wide disturbances - example 4



Plant-wide disturbances - example 5

- The refinery data set had 37 control loops (courtesy of a SE Asian refinery). The challenge was to automate detection of loops characterized by similar disturbances;
- Spectral principal components analysis identified 3 clusters representing 3 plant-wide disturbances.
- Noted: spectral PCA out-performed time-domain PCA because the spectra are invariant to time delays. For example, $\sin(\omega t)$ and $\cos(\omega t)$ have the same power spectrum.

Plant-wide disturbances - PCA 6

- Use FFT to derive power spectra.
- **X** is matrix of spectra, 37 rows and 512 columns.

512 frequency channels →
37 spectra, one for each tag ↓

- Method
  - Decompose **X** as a sum over basis functions $X = T \times W'$
  - The **T** vectors are the scores. The basis functions are the rows of the loadings matrix **W´**.
  - **W** is the eigenvector matrix of **X´X** and $T = X \times W$.

Plant-wide disturbances - PCA

7

- For a 3 - PC model:

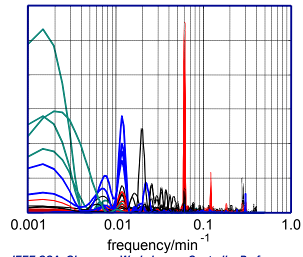
$$\boldsymbol{X} = \begin{pmatrix} t_{1,1} \\ \dots \\ t_{m,1} \end{pmatrix} \boldsymbol{w}'_1 + \begin{pmatrix} t_{1,2} \\ \dots \\ t_{m,2} \end{pmatrix} \boldsymbol{w}'_2 + \begin{pmatrix} t_{1,3} \\ \dots \\ t_{m,3} \end{pmatrix} \boldsymbol{w}'_3 + \boldsymbol{E}$$

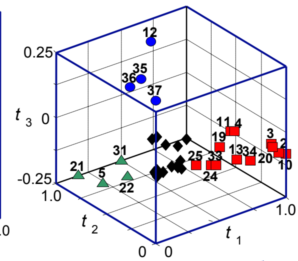
  - The n'th spectrum has scores $t_{n,1}$, $t_{n,2}$ and $t_{n,3}$. These are the weights in the summation of the **w´**- vectors needed to approximately reconstruct the n'th spectrum;
  - Plot the *t*-values to give 37 spots in a 3-D score plot;
  - Clusters represent process tags with similar spectra.

Plant-wide disturbances - PCA

8

- 3 term PCA model captured 90% of the variability in the spectra and identified clusters representing three plant-wide disturbances.

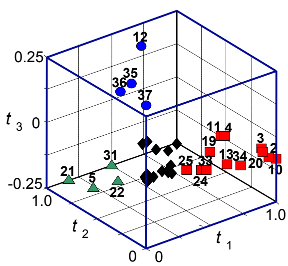




Plant-wide disturbances - PCA

9

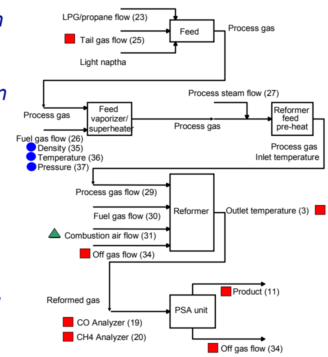
- PCA analysis:
  - Red squares:
    Oscillation at 0.06 min^{-1} (16.7 minutes per cycle);
  - Blue circles:
    Oscillation at 0.01 min^{-1} (100 minutes per cycle);
  - Green triangles:
    Tags with low frequencies and long slow deviations;
  - Black diamonds:
    Tags near (0,0,0) with no spectral features.



Plant-wide disturbances - PCA

10

- Process schematic with disturbances marked.
- 100 min oscillation is an upstream disturbance to fuel gas.
- 16.7 min oscillation is round the reformer, PSA unit and off-gas recycle.
- The challenge is to find the root cause.



Layout of the presentation

11

- Plant-wide disturbances
- Diagnosis of plant wide disturbances
  - Focus on finding limit-cycle root causes;
  - Signature for non-linearity that grow stronger closer to the root cause:
  - Application to refinery example.

Diagnosis - non-linear prediction

12

- Non-linearity test using surrogate data (Theiler et.al. 1992). Test the zero-order non-linear prediction error (Kantz and Schreiber ,1997). Tag with smallest error (highest predictability) is a candidate for the root cause.
- Surrogates have the same spectrum and auto-covariance as the time series being tested but are phase randomised.
- e.g. (Kaplan, http://www.macalester.edu/~kaplan/software)

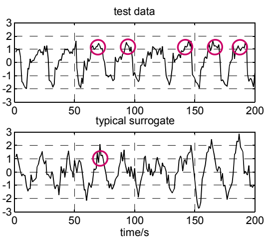
z = FFT(test data)

z = z *exp(jϕ) (where ϕ is random, 0-2π)

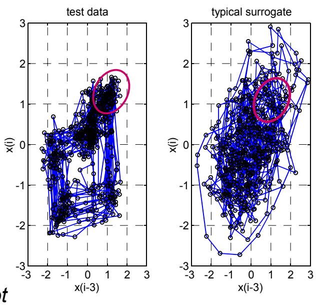
surrogate data = inverse FFT(z)

Diagnosis - non-linear prediction

Time trends



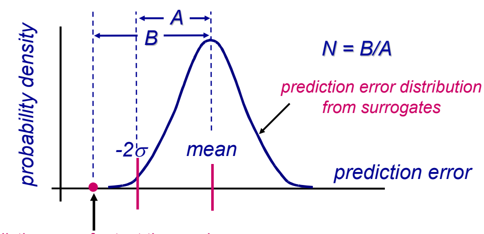
e.g. 2-D phase plane plots



Predictions are averages of near neighbours in phase plot

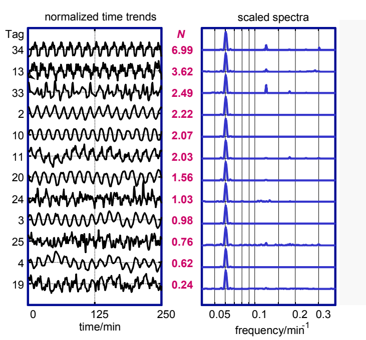
Diagnosis - non-linear prediction

- N is the negative offset from the mean in units of 2σ.
- N > 1 is interpreted as non-linearity in the time series.

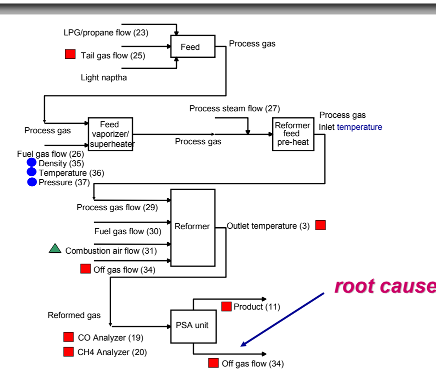


Diagnosis - results

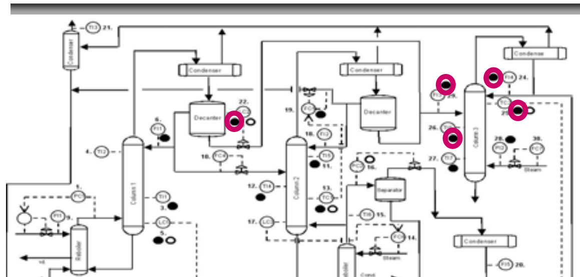
- Diagnosis of the 12 tags with the 17 min oscillation
- N suggests 34 as the root cause;
- 3, 4, 25 and 19 are furthest from the source, in terms of propagation.



Diagnosis - results



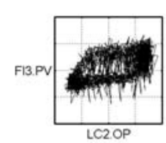
Diagnosis of valve stiction

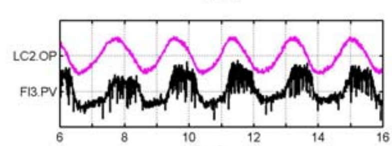


- Non-linearity was clustered round column 3;
- An upstream decanter level was non-linear;
- Deadband was found in Tag 22 control valve.

Diagnosis of valve stiction

- Check valve using pv-op map;
- The decanter LC valve has a deadband.





Diagnosis of valve stiction

19

- Literature on signatures for valve stiction:
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Conclusions

20

- Spectra offer a signature for classification of the nature of a time trend. Spectral PCA found clusters of similar spectra;
- Spectral PCA linked with the process schematic gave insights into plant-wide disturbances;
- A signature of non-linearity grew stronger closer to the source of disturbance;
- The signature identified the root cause;

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Literature cited

21

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