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ADVANCES AND NEW DIRECTIONS IN PLANT-WIDE DISTURBANCE DETECTION AND DIAGNOSIS

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Abstract: This article reviews advances in detection and diagnosis of plant-wide control system disturbances in chemical processes and discusses new directions that look promising for the future. Causes of plant-wide disturbances include non-linear limit cycles in control loops, controller interactions and tuning problems. The diagnosis of non-linearity, especially when due to valve stiction, has been an active area. Detection of controller interactions and disturbances due to plant structure remain open issues, however, and will need new approaches. For the future, the linkage of data-driven analysis with a qualitative model of the process is an exciting prospect. Finally, the paper offers some brief comments about emerging applications.

Keywords: fault detection; nonlinear time-series analysis; oscillation; performance analysis; plant-wide; process monitoring; process operation; signal analysis; whole-plant.

1. INTRODUCTION

Single-input-single-output control loop performance assessment (CLPA) and benchmarking is well established in the process industries [Qin, 1998; Desborough and Miller, 2002; Jelali, 2006]. The SISO approach has a shortcoming, however, because control loops are not isolated from one another. Specifically, the reason for poor performance in one control loop might be that it is being upset by a disturbance originating elsewhere.

The basic idea of process control is to divert process variability away from key process variables into places that can accommodate the variability such as buffer tanks and plant utilities [Luyben, Tyreus & Luyben, 1999]. Unfortunately, process variability is often *not* accommodated and it may just appear elsewhere. The reason for this is that modern industrial processes have reduced inventory and make use of recycle streams and heat integration. The interactions are strong in such processes because the amount of buffer capacity is small and the opportunities to exchange heat energy with plant utilities are restricted.

A plant-wide approach means that the distribution of a disturbance is mapped out, and the location and nature of the cause of the disturbance are determined with a high probability of being right first time. The alternative is a time consuming procedure of testing each control loop in turn until the root cause is found. Some key requirements [Qin, 1998; Paulonis, and Cox, 2003] are:

- Detection of the presence of one or more periodic oscillations;
- Detection of non-periodic disturbances and plant upsets;
- Determination of the locations of the various oscillations/disturbances in the plant and their most likely root causes.

A wish-list from Desborough and Miller [2002] included:

- Automated, non-invasive stick-slip detection in control valves;
- Facility-wide approaches including behaviour clustering;
- Automated model-free causal analysis;
- Incorporation of process knowledge such as the role of each controller.

The paper gives an overview of our own and others' work in detection and diagnosis of plant-wide control system disturbances. Detection of plant-wide disturbances is covered in Section 2 and the isolation and diagnosis of the root causes in Section 3. Both attempt a logical and structured classification and a comparative review of methods as well as highlighting open issues and unsolved problems. They are illustrated with a case study from a refinery. Section 4 discusses tests for sticking valves while Section 5 describes a new research direction involving the linkage of process information with data driven analysis using computer aided design data. Finally, Section 6 outlines some potential new areas of application.

2. PLANT-WIDE DISTURBANCE DETECTION

2.1 Classification of disturbances

<u>Timescales</u>: The first distinction in a classification of plant-wide disturbances concerns the timescale, which may be (a) slowly-developing, e.g. catalyst degradation or fouling of a heat exchanger, (b) persistent and dynamic, and (c) abrupt, e.g. a

compressor trip. The focus of this paper is on (b), dynamic disturbances that persist over a time horizon of hours to days. The approach is typically one of process auditing in which a historical data set is analysed off-line. The off-line approach gives opportunities for advanced signal analysis methods such as integral transforms and non-causal filtering.

Oscillating and non-oscillating disturbances. Figure 1 shows a family tree of methods for the detection of plant-wide disturbances and cites the references. The main sub-division is between oscillating and non-oscillating behaviours. An oscillation significant enough to cause a process disturbance can be seen in both in the time domain and as a peak in the frequency domain suggesting that either might be exploited for detection. The time trends at measurement points affected by a non-oscillating disturbance, by contrast, often look somehow similar but in a way that is hard to characterize because of the multiple frequencies which are present. The frequency domain readily reveals the similarities in the spectral content, however, and therefore spectra are useful for detection of non-oscillating disturbances. Some dynamic disturbances are not stationary. For instance, an oscillation may come and go or may change in magnitude. This localisation in time suggests that wavelet methods would be best for such cases.

2.2 Detection of oscillating disturbances

Methods for detection of oscillation fall into three main classes namely those which use the time domain, those using autocovariance functions (ACF), and spectral peak detection. Filtering or some other way of dealing with noise is usually needed in the time domain applications. A benefit of using the ACF is that the ACF of random noise appears at zero lag leaving a clean signal for analysis at other lags. The methods of Hägglund [1995], Thornhill and Hägglund [1997], Forsman and Stattin [1999], Miao and Seborg [1999], Thornhill, Huang and Zhang [2003], and Salsbury and Singhal [2005], should be able to detect oscillations such as those whose time domain, ACF and spectra are shown in Figure 3.

Most of the methods are off-line and exploit off-line advantages, such as the use of the whole data history to determine a spectrum or autocovariance function. The oscillation monitor of Hägglund (1995) is an on-line method and was implemented industrially in the ECA400 PID controller from Alfa Laval Automation which gave an alarm when as oscillation is detected.

The methods in Hägglund [1995,2005], Thornhill and Hägglund [1997], Forsman and Stattin [1999], Miao and Seborg [1999] and Salsbury and Singhal [2005] achieve the detection of an oscillation one measurement at a time, but more is needed for plant-wide detection than the detection of oscillations in individual control loops. It requires the recognition that an oscillation in one measurement is the same as the oscillation in another measurement, even though the shape of the waveform may differ and when interferences such as other oscillations are present. Characterization and clustering is needed in addition to oscillation detection. Thornhill, Huang and Zhang [2003] automated the detection of clusters of similar oscillations. An agglomerative classification algorithm from Chatfield and Collins [1980] detects the tags within each cluster and issues a report, an example of which is given in Table 1 (section 2.4).

2.3 Detection of multiple oscillations and non-oscillating disturbances

Persistent non-oscillatory disturbances are generally characterized by their spectra which may have broad-band features or multiple spectral peaks. The plant-wide detection problem requires (a) a suitable distance measure by which to detect similarity and (b) determination and visualization of clusters of measurements with similar spectra.

Spectral decomposition methods have been used to distinguish significant spectral features from broad-band noise that spreads all across the spectrum. Decomposition methods include principal component analysis, independent component analysis and non-negative matrix factorization. In all these methods, the rows of the data matrix $\mathbf{X}$ are the power spectra $P(f)$ of the signals and a spectral decomposition reconstructs the $\mathbf{X}$ matrix as a sum over p orthonormal basis functions $\mathbf{w}'_1$ to $\mathbf{w}'_p$ which are spectrum-like functions each having N frequency channels arranged as a row vector:

$$\mathbf{X} = \begin{pmatrix} t_{1,1} \\ \ldots \\ t_{m,1} \end{pmatrix} \mathbf{w}'_1 + \begin{pmatrix} t_{1,2} \\ \ldots \\ t_{m,2} \end{pmatrix} \mathbf{w}'_2 + \ldots + \begin{pmatrix} t_{1,p} \\ \ldots \\ t_{m,p} \end{pmatrix} \mathbf{w}'_p + \mathbf{E}$$

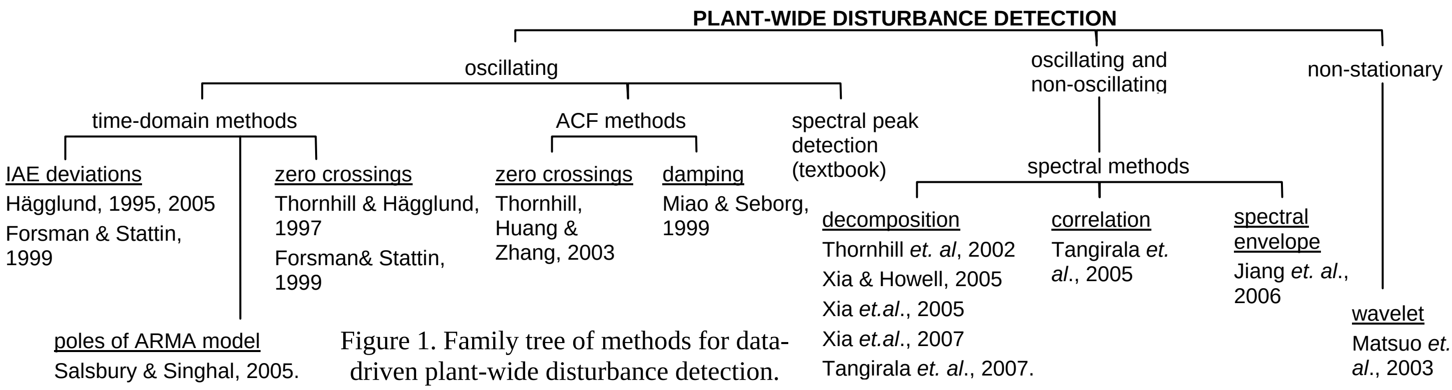

Figure 1. Family tree of methods for data-driven plant-wide disturbance detection.

The main distinction is the nature of the basis functions. In spectral principal component analysis (PCA) they are orthogonal functions with peaks at one or more frequencies. In the decomposition, the *i*'th spectrum in **X** maps to a spot having the co-ordinates $t_{i,1}$ to $t_{i,p}$ in a *p*-dimensional space. Similar spectra have similar *t*-coordinates and form clusters which can be detected using the Euclidian distance or the angles between vectors connecting the origin to each spot. Thornhill, Shah, Huang and Visnubhotla [2002] used spectral PCA to find clusters of measurements having similar spectra, detecting clusters of disturbances both with distinct spectral peaks and with multiple spectral features. Methods for display include a colour map [Tangirala, Shah & Thornhill, 2005] or a hierarchical tree [Thornhill and Melbø, 2006].

Spectral independent component analysis (ICA) minimises statistical dependence between the basis vectors. It gives spectral basis functions that have a higher one-to-one relationship with the physical sources of signals, as shown by Xia and Howell [2005] who gave the first application of ICA to process spectra. Non-negative matrix factorization (NNMF) was introduced in the area of image recognition [Lee and Seung, 1999]. In NNMF, every element in every basis function is either positive or zero, making it a natural choice for analysis of power spectra. NNMF has been reported for plant-wide disturbance analysis by Tangirala, Kanodia and Shah [2007] and by Xia, Zheng and Howell [2007]. The algorithms for spectral ICA and spectral NNMF are initialized with the basis vectors of spectral PCA.

Whilst all the decomposition methods give similar results at the clustering step, application studies have shown it is often the case that the basis functions in spectral ICA and NNMF yield a good characterization of the oscillations present because each tends to contain just one single spectral peak. They thus give a handle on diagnosis because the co-ordinates $t_{i,1}$ to $t_{i,p}$ indicate the strength of each spectral peak at the *i*'th measurement point. The performance of spectral ICA and NNMF in the diagnosis of broad-band disturbances having no distinct spectral peaks remains to be established, however.

Jiang, Choudhury, Shah, Cox and Paulonis [2006] used a spectral envelope method for detecting and categorizing process measurements with similar spectral characteristics. If the measurement time trends have unit variance, the spectral envelope value at a specific frequency is the largest eigenvalue of the power spectral density matrix at that frequency. It therefore makes use of the cross-spectra which enhances its ability to find common frequency components in a multivariate data set. It also gives diagnostic plots which indicate how each measurement point in the plant contributes at each frequency in the spectrum.

2.4 *Case study example*

The case study concerns the refinery separation unit of Figure 2. The reason for its inclusion is to illustrate the plant-wide concepts and to demonstrate that plant-wide disturbances can be solved. The upper panel in Figure 3 plots mean centred and normalized data with an oscillation in steam flow, analyser and temperature controller errors (*err*) and controller outputs (*op*). Measurements from upstream and downstream pressure controllers PC1 and PC2 are also included. The lower panel shows the power spectra. The sampling interval was 20s. The known reason for the oscillation is that the steam flow sensor in control loop FC1 was faulty. Condensate collected on the upstream side of the orifice plate until it reached a critical level, and the accumulated liquid would then periodically clear itself by siphoning through the orifice causing the plant-wide oscillation that can be seen in the data.

Table 1 gives the results of plant-wide oscillation analysis determined from the intervals between the zero crossings of the autocovariance functions in the middle panel of Figure 3 [Thornhill, Huang & Zhang, 2003]. Two plant-wide oscillations are reported because the most regularly oscillating tags in each group (with the smallest standard deviation) have oscillation periods that are different by more that the standard deviation of either (Tag 4 has 18.9 ± 1.5 and Tag 7 has 21.1 ± 1.1).

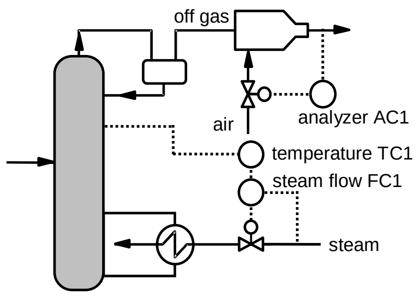

Figure 2. Process schematic.

Table 1. Oscillation analysis for the industrial case study.

tag analysis

tag no	period	tag no	period
1	20.4 ± 4.3	6	20.4 ± 4.3
2	20.9 ± 2.5	7	21.1 ± 1.1
3	19.1 ± 1.8	8	18.7 ± 5.5
4	18.9 ± 1.5	9	18.9 ± 3.9
5	20.9 ± 1.1	10	20.7 ± 1.4

automated cluster analysis

period	tags
18.9	4 3 9 8
20.7	7 5 10 2 6 1

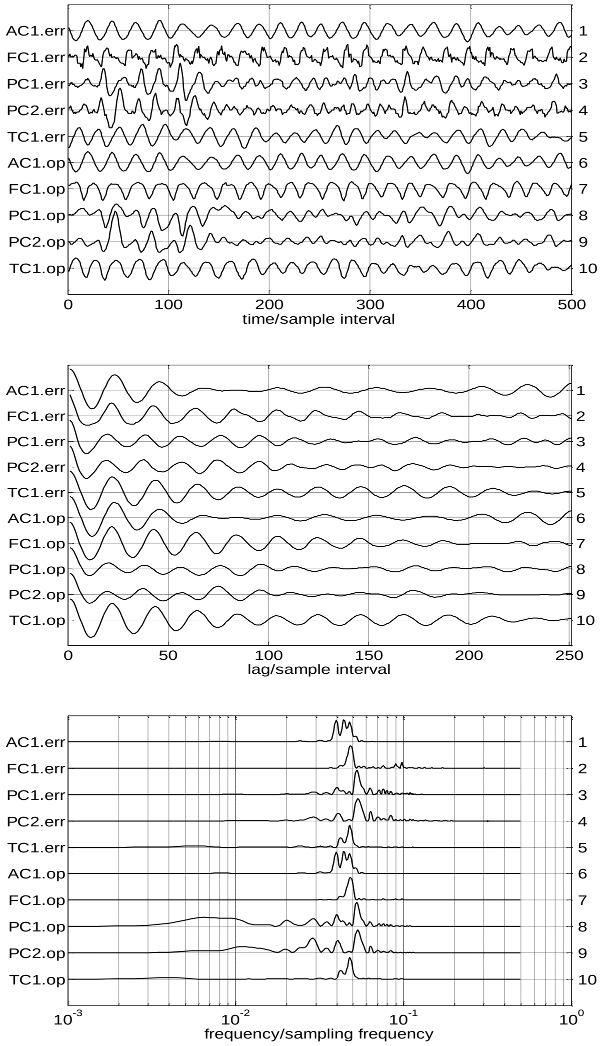

Figure 3. Data set. Upper panel: time trends. Middle panel: ACF. Lower panel: power spectra.

The results of spectral principal component analysis are shown in the form of a hierarchical tree in Figure 4 in which the spectrum of each tag is represented with a square symbol on the horizontal axis. The vertical axis represents a measure of the similarity or otherwise of the spectra. Similarity between the *i*'th and *j*'th spectra is assessed from their score vectors $\mathbf{t}_i' = \left(t_{i,1} \quad \ldots \quad t_{i,p}\right)$ and $\mathbf{t}_j' = \left(t_{j,1} \quad \ldots \quad t_{j,p}\right)$. If the spectra are similar the cosine of the angle θ between these vectors approaches +1, so $1-\cos(\theta)$ forms a measure of dissimilarity. Spectra form a cluster if they are connected to each other by short vertical lines. The tree shows two main clusters. Tags 3, 4, 8 and 9 have similar spectra (PC1 and PC2), as do 1, 2, 5, 6, 9, and 10 (FC1, TC1 and AC1). The wide separation of the spectral PCA clusters shows that the groups are distinctly different thus confirming the finding from oscillation analysis. Tags 1 and 6 are the controller error and controller output of AC1. AC1 at the top of the column is physically well separated from FC1 and TC1 (Tags 2, 5, 7 and 10), however, the tree shows it shares related dynamic behaviour because the spectra for 1 and 6 join the 2, 5, 7 and 10 cluster well below the top of the tree.

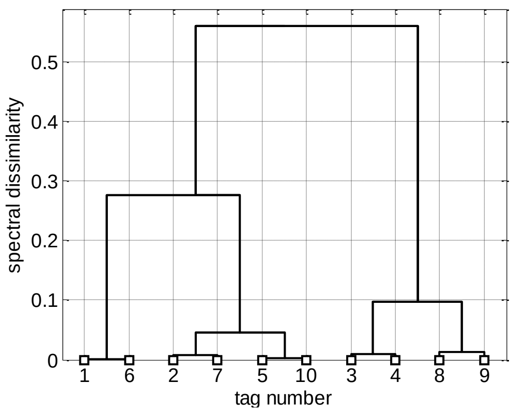

Figure 4 Spectral classification tree.

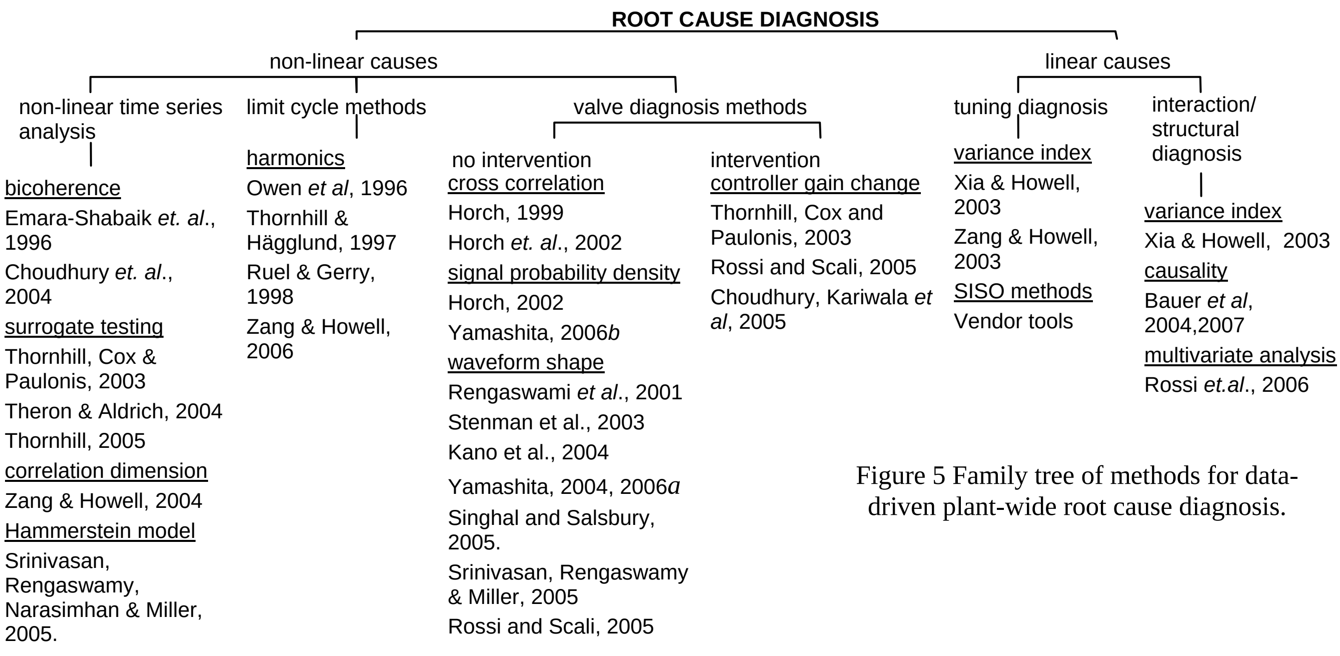

Figure 5 Family tree of methods for data-driven plant-wide root cause diagnosis.

3. ROOT CAUSE DIAGNOSIS

Figure 5 is a family tree of methods for the diagnosis of the root cause of a plant-wide disturbance. It focuses on data-driven methods using signal analysis on the measurements from routine operation. Alternative approaches that use process insights and knowledge are discussed in section 5. The main distinction in the family tree is between *non-linear* and *linear* root causes.

The diagnosis problem decomposes into two parts. Firstly the root cause of each plant-wide disturbance should be distinguished from the secondary propagated disturbances which will be solved without any further work when the root cause is addressed. The second stage is testing of the candidate root cause loop to confirm the diagnosis.

3.1 Finding a non-linear root cause of a plant-wide disturbance

Non-linear root causes of plant-wide disturbances include:

- Control valves with excessive static friction;
- On-off and split-range control;
- Sensors faults;
- Process non-linearities;
- Hydrodynamic instabilities such as slugging flows.

Sustained limit cycles are common in control loops having non-linearities. Examples include the stop-start nature of flow from a funnel feeding molten steel into a rolling mill [Graebe, Goodwin & Elsley, 1995] and variations in consistency of pulp in a mixing process [Ruel & Gerry, 1998]. Thornhill [2005] described a hydrodynamic instability caused by foaming in an absorber column. These examples show that disturbances due to non-linearity are not just confined to control valve problems, common though these are.

Non-linear time series analysis: A non-linear time series means a time series that was generated as the output of a non-linear system, and a distinctive characteristic is the presence of phase coupling between different frequency bands. Non-linear time series analysis uses concepts that are quite different from linear time series methods and are covered in the textbook of Kantz and Schreiber [1997]. For example, surrogate data are times series having the same power spectrum as the time series under test but with the phase coupling removed by randomization of the phase. A key property of the test time series is compared to that of its surrogates and nonlinearity is diagnosed if the property is significantly different in the test time series. Another method of nonlinearity detection uses higher order spectra because these are sensitive to certain types of phase coupling. The bispectrum and the related bicoherence have been used to detect the presence of nonlinearity in process data [Choudhury, 2004; Choudhury, Shah & Thornhill, 2004]. Root cause diagnosis based on non-linearity has been reported on the assumption that the measurement with the highest non-linearity is closest to the root cause [Thornhill, Cox & Paulonis, 2003; Thornhill, 2005; Zang & Howell, 2005]

Disturbance propagation: The reason why non-linearity is strongest in the time trends of measurements nearest to the source of a disturbance is that the plant acts as a mechanical filter. As the limit cycle propagates to other variables such as levels, compositions and temperatures the waveforms generally become more sinusoidal and more linear because plant dynamics destroys the phase coupling and removes the spectral harmonics which characterize a limit cycle oscillation. Empirically, non-linearity measures do very well in isolation of non-linear root causes. However, a full theoretical analysis is missing at present of why and how the various non-linearity measures change as a disturbance propagates, and this remains an open research question.

Limit cycles and harmonics: The waveform in a limit cycle is periodic but non-sinusoidal and therefore has harmonics which can be used to detect non-linearity.

It is not always true, however, that the time trend with the largest harmonic content is the root cause because the action of a control loop may split the harmonic content of an incoming disturbance between the manipulated variable and the controlled variable. Insight into the distribution of harmonic content is gained from the frequency responses of the control loop sensitivity and complementary sensitivity functions [Zang & Howell, 2005]. Matsuo, Tadakuma and Thornhill [2004] showed an example of a level control loop with an incoming disturbance from upstream which comprised a fundamental oscillation of about 46 samples per cycle and a second harmonic with 23-24 samples per cycle. The controlled variable (level) had a strong second harmonic at 23-24 samples per cycle while the manipulated variable contained only the fundamental oscillation with a period of 46 samples. Harmonic analysis would wrongly suggest the level controller as the root cause because of the strong second harmonic in the controlled variable. Non-linearity assessment, by contrast, correctly found the time trend of the disturbance to be more non-linear than those of the manipulated and controlled variables.

Case study example: Non-linearity testing using surrogate analysis showed the group of tags in Table 1 with the 21 samples per cycle oscillation period had non-linearity in the FC1 controller output, FC1 controller error and the TC1 controller output. These point unambiguously to the FC1 slave control loop as the source of the oscillation. This is the correct result, the FC1 control loop was in a limit cycle because of its faulty steam flow sensor. There was no non-linearity present in tags 3, 4, 8 and 9 associated with PC1 and PC2 and a root cause other than non-linearity has to be sought for their oscillation. A controller interaction is suspected because set point changes in PC1 (not shown) initiated oscillatory transient responses in both pressure controllers.

3.2 *Finding a linear root cause of a plant-wide disturbance*

A straw poll of industrial process control engineers in June 2005 at an IEE Seminar in the UK suggested the most common root causes, after non-linearity, are poor controller tuning, controller interaction and structural problems involving recycles. The detection of poorly tuned SISO loops is routine using commercial CLPA tools, but the question of whether an oscillation is generated within the control loop or is external has not yet been solved satisfactorily using only signal analysis of routine operating data. Promising approaches to date require some knowledge of the transfer function [Xia and Howell, 2003].

There has been little academic work to address the diagnosis of controller interaction and structural problems using only data from routine process operations. Some progress in being made, however, by cause and effect analysis of the process signals using a quantity called transfer entropy which is sensitive to directionality to find the origin of a disturbance [Schreiber, 2000; Bauer, Thornhill & Meaburn, 2004; Bauer, 2005; Bauer, Cox, Caveness, Downs & Thornhill, 2007]. Transfer entropy uses joint probability density functions and is sensitive to time delays, attenuation and the presence of noise and further disturbances that affect the propagating signals. The outcome of the analysis is a qualitative process model showing the causal relationships between variables.

<u>An example</u>: A study between BP and UCL used the method of transfer entropy with data from a process with a recycle, Figure 6. None of the time trends was non-linear and the causal map implicated the recycle because all the variables in the recycle were present in the order of flow. Knowing that the problem involves the recycle rather than originating with any individual control loop suggested the need for an advanced control solution.

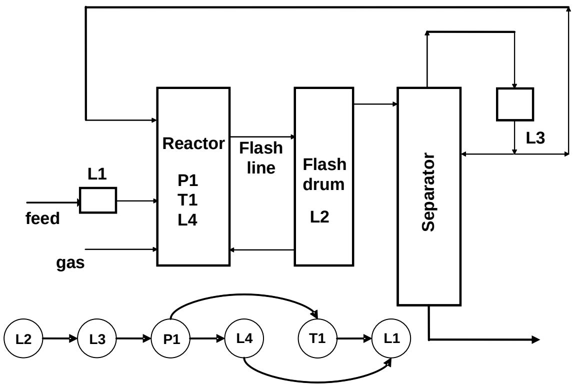

Figure 6. Cause and effect in a process with recycle (courtesy of A. Meaburn and M. Bauer).

4. VALVE TESTS

If a root cause has been isolated to a particular valve then further signal analysis is usually carried out before maintenance action is requested. Also, some alleviating actions may be taken to minimise the impact of the problem [Gerry and Ruel, 2001]. Figure 5 cites references for methods which have also been reviewed and benchmarked by Horch [2007]. Some general observations are discussed here.

<u>Stiction in valves</u>: Sticking control valves have dead band and stick-slip behaviour (stiction) caused by excessive static friction. *Deadband* arises when a finite force is needed before the valve stem starts to move while *stick-slip* behaviour happens when the maximum static friction required to start the movement exceeds the dynamic friction once the movement starts [Karnopp, 1985; Dewit, Olsson, Åström & Lischinsky, 1995; Olsson, 1996; Kayihan & Doyle III, 2000; Choudhury, Thornhill & Shah, 2005].

Control valve diagnosis is facilitated if the controller output signal, *op*, and either the flow through the valve, *mv*, or the valve position are measured. A *op-mv* plot is a straight line at 45 degrees for a healthy linear valve, and any deviations such as deadband can be diagnosed by visual inspection. Automated analysis of the *op-mv* plot can be problematical, however, due to the presence of noise, varying set point and the difficulty of maintaining a data base of all possible patterns for a match. In practice, the flow through the control valve is frequently *not* measured unless it is in a flow control loop. Similarly, the position, while it may be measured on a modern valve with a positioner, is not always available in the data historian. The challenge in analysis of valve problems, then, is to determine and quantify the type of fault present using *op* and *pv* data only. The *pv* is the measurement or controlled variable of the control loop, for instance the level in the case of a level control loop. The major difficulty is that the process dynamics (integration in the case of a level loop) greatly interfere with the analysis. Stiction in a loop with an integrating process can be detected by examination of the probability density function of the *pv* signal or of its derivatives [Horch, 2002; Yamashita, 2006*b*]. Several of the methods are reviewed in depth in Horch [2007] and compared on a benchmark data set. It is encouraging that several of them are able to utilize *op* and *pv* data successfully.

<u>The impact of the controller on the limit cycle</u>: It has been known for many years that control loops with sticking valves do not always have a limit cycle [McMillan, 1995; Piipponen, 1996; Olsson & Åström, 2001]. Choudhury, Thornhill and Shah [2005] derived the describing function of a non-linearity with deadband and stick-slip to gain insights. Table 2 lists the behaviour depending on the

process, controller and the presence or not of deadband and stick-slip.

Gerry and Ruel [2001] have reviewed methods for combating stiction on-line including conditional integration in the PI algorithm and the use of a dead zone for the error signal in which no controller action is taken. A short-term solution is to change the controller to *P*-only. The oscillation should disappear in a non-integrating process and while it may not disappear in an integrating process its amplitude will probably decrease. A further observation is that changing the controller gain changes the amplitude and period of the limit cycle oscillation. In fact, observing such a change is a good test for a faulty control valve. The aim is to reduce the magnitude of the limit cycle in the short term until maintenance can be carried out. In practice, since the expected change in amplitude and period is complicated to work out, one tries a 50% reduction in gain first or a similar increase in gain if the trend seems to be going the wrong way. More sophisticated control solutions for friction compensation have been proposed by Piipponen, [1996], Kayihan and Doyle III [2000], Hagglund [2002] and Srinivasan and Rengaswamy [2005].

Table 2 Limit cycles in control loops.

process and controller	deadband only	stick-slip
integrating, PI	limit cycle	limit cycle
integrating, P-only	no limit cycle	limit cycle
non-integrating, PI	no limit cycle	limit cycle
non-integrating, P-only	no limit cycle	no limit cycle

5. USE OF PROCESS INFORMATION

Qualitative process information is implicitly used in diagnosis when an engineer considers the results from a data-driven analysis. An exciting possibility is to capture and make automated use of such information. Qualitative models include signed digraphs (SDG) [Venkatasubramanian, Rengaswamy & Kavuri, 2003; Maurya, Rengaswamy & Venkatasubramanian, 2004; Srinivasan, Maurya & Rengaswamy, 2006], Multilevel Flow Modelling [Petersen, 2000] and Bayesian belief networks [Weidl, Madsen & Israelson, 2005]. Chiang and Braatz (2003)] and also Lee, Song & Yoon (2003) showed enhanced diagnosis using signal based analysis if a qualitative model is available.

We believe that qualitative models of processes will in future become almost as readily available as the historical data. The technology that will generate such models is already in place in Computer Aided Engineering tools such as ComosPT (Innotec) and Intools (Intergraph). The plant topology in a process diagram can now be exported into a vendor independent and XML-based data format, giving a portable text file that describes all relevant equipments, their properties and the connections between them [Fedai and Drath, 2005]. The Standard is described in DIN V 44366 (2004) and IEC/PAS 62424 (2005) which is called Computer Aided Engineering Exchange (CAEX) and which specifies an XML schema. ISO-15926-7 is a similar standard.

A prototype tool that links a CAEX description with a data-driven analysis has been demonstrated [Yim, Ananthakumar, Benabbas, Horch, Drath & Thornhill, 2006]. Its aim is to parse and draw conclusions from an electronic process schematic. When linked with data-driven signal analysis of process measurements the end result is a powerful diagnostic tool for isolating the root causes of disturbances. The features are:

- Capture of process connectivity description using CAEX;
- Parsing and manipulation of the description;
- Linkage of plant description and results from data-driven analysis;
- Testing of root cause hypotheses;
- Logical tools to give root cause diagnosis and process insights.

A reasoning engine finds physical paths and control paths in the plant and connections between items of equipment, and determines root causes for the measured plant-wide disturbances. For example, detection of non-linearity in the time series of the process measurements suggests a non-linear root cause such as a sticking valve. In the case of ambiguity then the reasoning engine automatically highlights the non-linear measurement point further upstream as closer to the root cause. It can also verify that there is a feasible propagation path between a candidate root cause and all the other locations in the plant where secondary disturbances have been detected.

6. NEW APPLICATION AREAS

Plant-wide detection and diagnosis is starting to have an impact in areas outside process systems such as power plants, electricity transmission systems and supply chains. The techniques often map across without difficulty after adjustments for the timescales, for instance inter-area oscillations in electricity transmission typically have periods of 2 to 5 seconds while in manufacturing supply chains the oscillations have periods of weeks to months. The main challenge in successful transfer of the methods is in acquiring domain specific knowledge such as what faults are typical of the target system, and the business needs and drivers.

Power plant applications: Odgaard and Trangbaek (2006) compared measurement-based methods for detection of oscillation in a coal-fired power generation plant. A key finding was that transient components in the signals caused false detections with many of the methods described earlier. A power plant is a utility and its function is to respond to load changes so as to maintain constant voltage and frequency. Operating conditions change frequently in order to provide this service and transients are therefore common. More work will be needed to distinguish oscillations under transient conditions. The examples presented by Odgaard and Trangbaek [2006] also showed intermittent oscillations present under some operating conditions and not others. A responsive, on-line oscillation detector would therefore be useful for power plant applications to detect when an oscillation has recently started.

A total process approach to power plant control system monitoring has been proposed by Horch [2005] to detect plant-wide swings and oscillations. The study considered what detection and diagnosis of plant-wide disturbances would have to offer over the existing condition monitoring of individual components such as turbines, boilers and pumps. It discussed equipment problems for which no condition monitoring is available and successfully tracked down a troublesome oscillation to a valve with a deadband.

Electricity transmission: A Report to Congress from the US Department of Energy in February 2006 highlighted deficiencies in the monitoring of the power transmission grid as making a key contribution to the seriousness of the August 2003 blackout in the USA and Canada. A requirement for daily operation is for on-line assessment of the damping status of a transmission network. Tools such as the Psymetrix StormMinder PDM [Golder & Wilson, 2004] use fast SCADA data, where available, to determine local damping and decay times and to find the origin of an upset condition by looking at the strength of its spectral signature. These measurement-based analyses are similar to those described in this paper suggesting that cross-fertilization of the ideas would be productive. The methods will have to be robust towards non-stationary and transient operation, as with power generation.

Data collection is challenging because in many locations the only data available in a network control centre are slow (5sec/0.2Hz) SCADA indicators of such things as transformer tap position and relay status. Power flows are available only as averages and steady state bus voltage magnitude and angle are inferred from model-based state estimation. Another issue is the accurate time-stamping of data collected over a very wide geographical area. Finally, the compilation of data from different commercial organizations can be a challenge because generating companies own the measurements of generator speed and rotor angle, while the transmission company owns the voltage, current and bus angle measurements.

Supply chain: Business needs in the operation of process and manufacturing supply chains have been widely discussed [e.g. Shah, 2005; Geary, Disney & Towill, 2006]. Issues include the removal of demand amplification (also known as bullwhip) and rogue seasonality. Rogue seasonality is an oscillation in inventory, orders and deliveries to customers induced by internal business practices. Demand amplification occurs in multi-echelon chains when replenishment rules magnify small variations in end-customer demands into large amplitude variations for upstream suppliers. There is much activity in supply chain modelling and design, but so far little use of the data from supply chain operations has been reported. Lapide [2000] reviewed several data-driven performance metrics such as added value and total cycle time, however the dynamic aspects of operation were not considered. Signal-based analysis of dynamic supply chain data should offer the capability to relate the supply chain dynamics to business practices and replenishment rules. An exploratory study [Thornhill and Naim, 2006] used spectral PCA to detect seasonal endogenous and exogenous disturbances in a steel industry supply network. The study used five years of weekly averages of sales, shipments and inventories. Open challenges are for companies to exploit daily or hourly data to capture more rapid dynamic effects, and for on-line signal analysis methods to detect emerging unwanted behaviour as it arises.

7. SUMMARY

Section 1 listed some industrial requirements and a wish-list for plant-wide controller performance assessment. The work reviewed in this paper has shown good progress towards these targets especially in detection of plant-wide disturbances and behaviour clustering. Non-linear root causes can now be located and distinguished from secondary propagated disturbances using analysis of signals from routine operation, with a high chance of being right first time. Stiction detection in valves has had much attention with several methods starting to perform well even in the difficult situation where no manipulated variable is measured. The isolation of linear root causes such as controller interactions and recycle dynamics is an open area still needing attention, however. Finally, we believe the linkage of plant layout information with signal analysis is due to take a big step forward using new Standards for description of plant layouts.

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