DETECTION AND DIAGNOSIS OF OSCILLATION IN CONTROL LOOPS

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Abstract: Previous work presented a real-time algorithm for the detection of oscillations in PI and PID feedback control loops. This paper examines further opportunities for oscillation detection in the off-line analysis of ensembles of data from control loops. Its use with measurements from routine operations is emphasised.

The paper presents operational signatures that indicate the cause of an oscillation. Typically, a full diagnosis requires a special test for which the loop is taken out of routine operation. The signatures lead to recommendations about which special test is most appropriate. They therefore reduce the time spent in trouble-shooting by guiding the choice of test.

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1. INTRODUCTION

Studies of the performance of single-input-single-output (SISO) control loops have shown that reasons for poor performance include both poor tuning and equipment problems such as sticking valves (Åström, 1991; Ender, 1993; Hägglund, 1995). Oscillations of the process variable either side of the set-point value gives particular cause for concern. Reducing or removing such oscillations yields commercial benefits (Martin *et al.*, 1991) because any reduction in variability means that set points can be held closer to an optimum constraint without the danger of violating that constraint. Hägglund's previous paper (Hägglund, 1995) described a method for the real-time detection of oscillation, and its incorporation into the ECA400 autotuning PID control module from Alfa Laval Automation. The control module generates an alarm when oscillations are detected.

Hägglund (1995) presented a flow chart for decision making. In this paper the flow chart has been augmented to make use of off-line oscillation detection and additional operational signatures. The flow chart directs the control engineer towards the tests most likely to confirm the diagnosis and to fix the problem.

An approach to control-loop performance assessment (CLPA) has been described by MacGregor (1988), Harris (1989) and Desborough and Harris (1992). An

advantage of CLPA is that it provides figures of merit for the performance, which can be derived during routine running without taking loops off-line for special tests. These methods are becoming widely implemented in the petrochemical and chemical sectors (Stanfelj *et al.*, 1993; Kozub and Garcia, 1993; Thornhill *et al.*, 1996) and also in the pulp and paper industry (Perrier and Roche, 1992; Lynch and Dumont, 1996; Jofriet and Bialkowski, 1996; Owen *et al.*, 1996).

Oscillation detection and CLPA can complement one another. The context for CLPA assessment is an ensemble of historical data, for example over the past 24 hours. The same data ensemble is suitable for the oscillation analysis described in this paper. Moreover, the CLPA algorithm provides filtering of the data, and determines the noise component of the controller error. The significance of a deviation from set point can thus be assessed from the ratio between the deviation and the r.m.s. value of the noise. This paper describes enhancements derived from applying the oscillation-detection method in a CLPA setting.

Operational signatures can be found within routine operating data. Pryor (1982) presented the use of the power spectrum in the analysis of process data. Desborough and Harris (1992) used the power spectrum to conclude that control loops had a long-term deviation from set point, and also to highlight an oscillatory loop, while Tyler and Morari (1996)

have demonstrated a spectral signature arising from a disturbance. A contribution of this work is to show that the power spectrum can distinguish between a tuning problem and a limit-cycle oscillation due to non-linearity such as valve friction. Plots of set point (*sp*) against process variable (*pv*) for loops in a cascade configuration also show characteristic patterns that pinpoint the type of non-linearity.

The procedures presented here focus on the analysis of oscillations arising within the loop itself. They do not positively indicate when the origin of an oscillation is a disturbance; the only indication of a disturbance is the lack of an alternative explanation. Several authors have reported success in the analysis of disturbances from routine operating data, and it is therefore necessary to explain why the approach reported here does not do so.

Stanfelj *et al.* (1993) provided a decision-making tree which included cross-correlation between a feed forward signal and the controlled variable of the loop under analysis. Likewise, Owen *et al.* (1996) showed an application of control-loop performance monitoring which accounts for upset conditions of the whole mill and interactions between control loops. These cases needed a knowledge of the process flowsheet, in particular about which loops might disturb one another. In this paper, by contrast, the focus is on the analysis of an individual SISO loop so that the methods can remain feasible for implementation in a stand-alone module. No knowledge of the layout of the rest of the process flowsheet has been taken for granted, and therefore the feedforward approach to the analysis of disturbances has not been used.

Ten refinery control loops have been selected to illustrate the methods. These are exceptional examples and are in no way representative of the majority of non-oscillating and well-tuned control loops in the refineries in question. Indeed, the oscillatory loops were readily identified for the project because they were already under investigation. The authors are grateful to the industrial partner for the chance to use these examples.

The paper is laid out under two main sections. Section 2 describes detection and characterisation of oscillations, while Section 3 explains how the causes of oscillations may be diagnosed. Each section is illustrated with examples from the ten refinery control loops. Section 4 gives the conclusions.

2. DETECTION AND CHARACTERISATION OF OSCILLATIONS

2.1 Techniques

Real-time oscillation detection. The real-time oscillation-detection method presented by Hägglund

(1995) calculates the integrated absolute deviation (IAE) between successive zero crossings of the controller error signal. Its motivation is that when the controller error is oscillatory rather than random, such deviations are large and the intervals between them are long. An oscillatory signal therefore has larger IAE values than a random one. The IAE is defined by the following expression:

$$IAE_i = \int_{t_i}^{t_{i+1}} |Y(t)| dt$$

where $Y(t)$ is the controller error signal and t_i and t_{i+1} are times of successive zero crossings of $Y(t)$.

These integrated deviations are compared to a threshold value which is the IAE value of a sinusoidal oscillation having an amplitude a . Choice of the presumed oscillation frequency ω_{osc} is discussed by Hägglund (1995), a good choice being $2\pi/\tau_i$. τ_i is the controller integration time as used in the following generic expression in which the PI control signal is derived from the error signal, the controller gain K and τ_i :

$$K \left(Y(t) + \frac{1}{\tau_i} \int Y(t) dt \right).$$

Since Hägglund's real-time algorithm is embedded within a 'smart' control module, the integration time is always known. The basis for the choice of ω_{osc} is that in a well-tuned controller the cross-over frequency (ω_{180}) at which the oscillation occurs is similar to $2\pi/\tau_i$. The IAE value over a cycle of oscillation for a sine wave $a \sin(\omega_{osc} t)$ is $2a/\omega_{osc}$ and the condition for detection of a single deviation of amplitude a is therefore:

$$IAE_i \geq 2a/\omega_{osc} = a\tau_i/\pi.$$

In the real-time method oscillation is detected as the condition in which the integrated deviations persistently exceed the threshold, with a set to one percent of the controller range over a supervision time of 50 times the presumed oscillation period.

Loop performance assessment. The method of control-loop performance assessment (CLPA) described by Desborough and Harris (1992) is outlined here. The basis of CLPA is that the controller error should have no predictability over some given prediction horizon. That is to say, the controller error sequence Y is decomposed as:

$$Y_i = \hat{y}_i + r_i$$

where $\hat{y}$ is the predictable component of the controller error and r the zero mean residuals.

The aim of control is to remove any predictable components. That is, $\hat{y}$ should be small or zero. A common cause of a predictable component is a persistent oscillation, in which case an oscillation-detection procedure can offer to CLPA an indication of the reason for the loss of performance. Desborough and Harris's performance index can be expressed as:

$$\eta = \frac{mse(\hat{y}_i)}{mse(Y_i)} = 1 - \frac{\sigma_r^2}{mse(Y_i)}$$

with $mse(\hat{y}_i)$ being the mean square value of the predictable component, $mse(Y_i)$ the mean square value of the controller error and σ_r^2 the variance of the (zero mean) residuals.

The index η is dimensionless and in the range [0 1]. When the control performance is good the controller error has little predictability and the index is 0 because $mse(Y_i) = \sigma_r^2$. The opposite is true for a poorly controlled loop in which the controller error is predictable.

The predictable component is determined from an autoregression model that makes predictions b steps ahead:

$$\hat{y}(i+b) = a(0) + a(1)Y(i) + a(2)Y(i-1) + \dots + a(m)Y(i-m+1).$$

The above model is fitted to an ensemble of n samples of the controller error using a least-squares fit procedure. Thornhill *et al.* (1996) discuss the implementation of the above algorithm in a refinery setting, and give recommendations for the parameters b and m .

Off-line oscillation detection. As mentioned earlier, real-time detection of oscillations requires two controller parameters to be known, namely τ_i and the output range. This requirement poses no problem for a real-time algorithm embedded within a modular control unit. For off-line use, however, alternatives may be assessed from the data set itself. For instance, the oscillation-detection procedure can make use of the predictable component and the r.m.s. values of the residuals (σ_r) that are provided by the CLPA algorithm. Then the significance of a deviation is assessed relative to σ_r , rather than the absolute criterion of one percent of the range. Note, however, that the prediction horizon, b , needed by the CLPA assessment is not necessarily the optimum prediction horizon for the oscillation detection. This point is discussed shortly.

The intervals between zero crossings are also useful in the assessment of the significance of the deviation. The off-line condition for a significant deviation relates the mean value of IAE over an interval ΔT to the r.m.s. value of the noise:

$$\frac{IAE_i}{\Delta T_i} \geq \sigma \cdot \xi \quad \text{or} \quad \frac{IAE_i}{\sigma \cdot \Delta T_i} \geq \xi$$

where ΔT_i is the time interval between the zero crossings, equal to $t_{i+1} - t_i$, σ is an estimate of the r.m.s. value of the noise and ξ is a threshold for detection.

For instance, suppose it is desired to detect sinusoidal oscillations having unit amplitude in the presence of noise having an r.m.s. value of 1. The threshold for detection should therefore be set to $2/\pi$, which is the mean value of a full wave rectified sinusoidal waveform. The threshold can also be set to other values to suit other purposes, as described below. However, the $2/\pi$ threshold is an important one used to assess the significance of oscillations detected using other thresholds.

It is desirable to evaluate the deviations using the predictable component of the controller error signal because the filtering removes noise. The work presented in this paper obtains the predictable component of the signal using the autoregressive time-series model, since that filter is used in the CLPA algorithm.

It has proved best to use a prediction horizon, b , equal to one sample interval. By contrast, the CLPA analysis of Desborough and Harris (1992) is made over a prediction horizon that reflects the time delay within a control loop in order to make the CLPA index a benchmark of minimum-variance control. For a loop with a persistent oscillation there is little difference between the two cases. However, for a loop where the oscillation tends to lose coherence after a few cycles, as in a mildly resonant loop driven by white noise, the shorter prediction horizon better reflects the deviations due to the oscillation. The same is true of deviations caused by random disturbances.

Assessment of regularity, amplitude and period of oscillation. Figure 1 shows an example of a simulated signal comprising a unit amplitude sinusoidal signal with added noise having an r.m.s. value of 1.5. It shows the deviations measured as $IAE/(\sigma \cdot \Delta T)$ plotted at the times t_{i+1} and also shows the threshold value at which the pattern of deviations in the predictable component is most regular. At lower thresholds the pattern of deviations is more random, while if the threshold were higher some of the deviations would not cross it, thus disrupting the regular pattern.

Regularity is assessed by the use of a statistic, q , termed the *regularity factor*. It is derived from the sequence of ratios between adjacent intervals Δk at which deviations cross the threshold. Thus:

$$R_i = \frac{\Delta k_{i+1}}{\Delta k_i}$$

and the dimensionless regularity factor, q , which depends on the threshold, is:

$$q(\xi) = \frac{\text{mean value of } R}{\text{standard deviation of } R}.$$

Fig 1. The analysis of a unit amplitude sinusoidal signal with simulated noise having r.m.s. value of 1.5

For instance, in Figure 1 suppose the threshold is 0.39. There is a deviation exceeding that threshold at sample interval 480, another at sample interval 559 and another at 642. Thus $\Delta k_{i+1} = 83$ and $\Delta k_i = 79$ and the ratio of these two is $R_i = 1.05$. Smaller deviations such as the ones at samples 573 and 436 are not counted as they do not exceed the threshold. The lower left plot in Figure 1 shows the regularity factor plotted against the threshold for this particular data set.

When the intervals between deviations are regular, the ratios cluster around the value of 1, and the spread of values either side of 1 (the standard deviation) is small. Thus, for regular oscillations the regularity factor is larger than for a random distribution of the Δk intervals. It has not proved possible to determine the sampling distribution of q because the Δk intervals are integers. The distribution is thus discontinuous, and cannot easily be used for testing of a hypothesis of randomness in the deviations. Nevertheless, q serves well as a qualitative regularity factor even though it does not have a rigorous statistical interpretation. Signals judged by eye to have regular oscillations have values of q above about 1.3.

The value of the threshold for which the pattern of deviation is most regular is noted. It is a dimensionless quantity that can be interpreted as the ratio between the amplitude of the oscillating signal and the r.m.s. value of the noise. As noted earlier, $2/\pi$ is the theoretical threshold for detection of a unit amplitude sinusoidal oscillation in the presence of noise having an r.m.s. value of 1. In Figure 2 the threshold at which the deviations are most regular is 0.39. This is close to 0.42, which is the value expected for the quantity $IAE/(\sigma \cdot \Delta T)$ for a unit amplitude sinusoidal oscillations when σ is 1.5.

The period of the oscillation T_p is determined from:

$$T_p = 2 \frac{k_n - k_1}{n - 1}$$

with $n-1$ the total number of intervals between deviations that cross the threshold. The positions of the first and last deviations are k_1 and k_n .

Table 1. Details for ten refinery control loops with CLPA results and characterisation of oscillation

Loop description and expert analysis	η	ξ	q	T_p /samples	
				Auto	Visual
<u>Loop 1:</u> Level master loop. Thought to be affected by a valve with a deadband in the slave flow loop.	0.80	9.76	1.23	105	184
<u>Loop 2:</u> Liquid flow slave loop for loop 1. Thought to have a valve with a dead band.	0.90	2.68	1.42	100	184
<u>Loop 3:</u> Liquid flow loop, slave in cascade control. Thought to have a valve with stick-slip characteristics.	0.67	2.01	3.96	213	218
<u>Loop 4:</u> Very oscillatory pressure-control loop. Origin of oscillations is unknown.	0.85	2.47	4.43	13.2	12.4
<u>Loop 5:</u> A well-tuned temperature loop in which the steam flow valve is known to be oversized.	0.05	0.44	1.41	13.0	12.5
<u>Loop 6:</u> Pressure-control loop. Oscillations thought to be due to tuning problem.	0.36	0.55	2.18	19.6	21.4
<u>Loop 7:</u> Liquid flow loop, slave in a cascade control. Oscillations thought to be due to tuning problem.	0.43	0.56	1.72	18.5	17.3
<u>Loops 8-9:</u> A liquid flow loop at two experimental tuning settings. Loop has no hardware faults.	0.16 0.05	0.17 0.05	1.42 1.17	13.5 12.8	11.5 -
<u>Loop 10:</u> Level-control loop on a surge vessel subject to load disturbances.	0.57	0.89	0.92	199	-

Fig 2. Predictable components and normalised deviations. The thresholds at which the patterns of deviations are most regular are shown.

2.2 Application of oscillation detection to refinery control loops

Data for the applications. The applications reported here use data from SISO control loops from oil refineries. All the data ensembles have 1400 samples except loop 3 (1000 samples), and the analysis is done using all the samples even though, as in Figure 2, fewer may be plotted in order to show details more clearly. Table 1 outlines the features of the refinery data sets. Special points to note are that loops 1 and 2 are a master-slave cascade and that loops 8 and 9 are the same liquid flow loop with different tuning settings. The loops fall into the following categories:

- Loops thought to have a valve fault
- A loop that has been well tuned in spite of a known valve fault
- Loops having suspected tuning faults
- A loop having two large deviations known to be caused by disturbances
- A loop showing oscillations of unknown origin.

The data sets are sub-sampled compared to the sampling period used by the real-time distributed control system (DCS). Whereas the control algorithms iterate every second or every half second, the data are logged for the off-line analysis less frequently. The data trends have been examined for signs of aliasing - the oscillations are characterised in all cases by 12 samples or more, and are judged to be the fundamental oscillations, not the result of beating between the data-logging frequency and an undetected higher-frequency oscillation.

Characterisation of oscillations. Table 1 presents results for the selected refinery loops. It gives the regularity factor (q) and the threshold (ξ) at which the deviations are most regular. A threshold exceeding $2/\pi$ indicates that the amplitude of the oscillating signal is greater than the r.m.s. value of the noise, but the regularity factor is heuristic and does not have a mathematical interpretation. Table 1

Fig 3. Characterisation of oscillations for loops 1-10 in terms of regularity, threshold and CLPA index.

also gives the CLPA index (η) for each loop's performance.

Figure 2 shows examples of the analysis for selected loops, while Figure 3 plots the oscillation characterisations. In it, there are four distinct groupings:

- Loops 3 and 4 - high η , high q and large ξ .
- Loops 1, 2 and 10 - high η , low q and large ξ .
- Loops 6 and 7 - mid η , medium q and medium ξ .
- Loops 5, 8 and 9 - low η , low q and small ξ .

On the basis of what is known *a-priori* about the refinery loops it is observed that loops with problems have a threshold value greater than $2/\pi$, or a regularity factor greater than 1.3, or both. The following comments give some insight into these observations.

Loops with known valve faults (1, 2 and 3) have threshold values above $2/\pi$, while those with tuning problems (6 and 7) have threshold values below $2/\pi$. An explanation for the high threshold in the first case may be that the limit cycle oscillations due to valve faults are self-generated within a loop by the non-linearity and are often highly predictable (i.e., they have a high signal-to-noise ratio). A poorly tuned loop with an overly resonant tuning setting, on the other hand, oscillates because it is 'ringing' at its natural frequency when excited by process or sensor noise. It is therefore likely to have a lower signal-to-noise ratio.

Loop 10 has large deviations, but they are irregular. It is known to be subject to random disturbances and it is therefore to be expected that its regularity factor is the lowest of all the loops.

Since loops 1 and 2 are influenced by a valve non-linearity, it is a surprise to find that the limit cycle is not especially regular. Evidence for the low regularity factor can be seen in the time trend, as discussed in the next sub-section, and seems to suggest that the valve non-linearity does not behave reproducibly from one cycle to the next.

Loop 5 is known to have a hardware problem. However, the loop has had attention from control experts, and is as well tuned as it can be. As a result, the oscillatory component of its controller error signal is smaller than the noise component and the threshold value is below $2/\pi$. The heuristic guideline given above makes it possible to use the characterisation of the oscillation in the diagnostic procedure (Section 3.1), but the ambiguous results for loops 1, 2 and 5 show that it should be used with caution.

Period of oscillation. Table 1 also presents the period of the detected oscillations, and the period assessed by visual inspection. In most cases the oscillation-detection routine found a period of oscillation close to the one assessed by the experts. There are some instance where the expectations have not been matched.

In the case of loop 2 the spectral analysis presented later (Section 3.2) shows that the controller error signal has a strong second harmonic. It is likely that the procedure has found the second harmonic rather than the fundamental component. However, the spectrum of loop 1 shows that the signal has a fundamental period of 180 sample intervals, which is close to the visual assessment. The automated procedure therefore failed to evaluate the oscillation frequency correctly for loop 1. The reason is that the regularity factor is too low. As seen in Figure 2, the controller error of loop 1 is not symmetrical, with the positive-going deviations being smaller than the negative-going ones, while even deviations in the same direction are not all of the same size. The visual assessment of other loops with low regularity factors (loops 9 and 10) failed to see any convincing oscillation. The conclusion is that although the procedure gives a value for T_p in all cases it can only be used with confidence when the regularity factor exceeds 1.3.

Enhancements to real-time oscillation detection. The benefit of an enhanced real-time oscillation-detection algorithm is illustrated in the case of a level-control loop having P-only control. In the case of the level-control loop 1 the lack of a value for τ_i rules out its use in the detection threshold for the real-time algorithm. Use of ΔT_i , the time between zero crossings, in the criterion for detection of oscillations provides an alternative means to generate a threshold

Fig 4. Flow charts for diagnosis and off-line tests.

for real-time detection of deviations. The criterion for detection of a 1 percent deviation becomes:

$$IAE_i \geq 2\Delta T_i / \pi$$

That is, the local period of oscillation is taken to be $2\Delta T_i$ instead of τ_i .

The use of $2\Delta T_i$ in place of τ_i also has benefits when the data are sub-sampled. Such a case might arise if the real-time oscillation detection were to reside in the plant information system layer of a DCS rather than in the PID layer, because the data may be sub-sampled in order to reduce traffic across the communications link. In sub-sampling, the value captured at the sample instant is held constant until the next sampling instant and the IAE value calculated by integration from sub-sampled data can therefore be larger than expected. The effect gets worse as the sub-sampling period becomes longer. If the sub-sampling interval is close to the controller integration time then a deviation may be detected after just one sample. Therefore, the use of the alternative time-scale parameter ΔT_i is again helpful.

When the controller output range is unknown, the detection of oscillations is enhanced by use of the r.m.s. value of the noise as a scaling parameter. Of course, the range is recorded with other loop parameters in the DCS, but assessing a scaling factor from the data reduces the dependence on extraneous information. For on-line use, the noise assessment would need to be assessed over, say, the past 24 hours using a recursive method of filtering. These observations show that the on-line detection method

can be applied in cases when neither the controller tuning settings nor the range of the process variable are known, and that it can also be used for sub-sampled data. Its applicability has therefore been extended to a wider range of cases.

3. DIAGNOSIS OF OSCILLATIONS

3.1 Techniques

Certain signatures give indications of the cause of an oscillation. They include:

- Interpretation of the CLPA index, regularity factor and oscillation-detection threshold.
- Examination of features in the power spectrum of the controller error. The power spectral density of the data ensemble is computed using the Welch method (1967).
- Dynamic *sp-pv* maps for loops where the set point changes often, such as loops in cascade mode.

The diagnosis procedure uses the above indicators from routine operating data to guide a process control engineer towards suitable special off-line tests. The following conclusions follow from the operational signatures, as shown in the flow chart in Figure 4(a):

- That an oscillation is present
- That an oscillation is due to poor tuning
- That an oscillation is due to limit cycling caused by a discontinuous non-linearity
- That (if no other indication is present) there may be a disturbance.

Fig 5. Power spectra of controller errors for selected loops.

Indications from more than one signature lead into each decision block. Some are clear-cut and are shown as unshaded items on the flow chart. If one or more of these indications is present, one can have considerable confidence in the decision. Others, shown in grey shading, are less clear-cut because they can be ambiguous. A decision based only on grey indications is less convincing. In the following text the signatures in the unshaded and shaded blocks will be called *clear* and *grey* signatures respectively.

Special tests on the control loop are proposed for the diagnosis, as shown in the flow chart 4(b). This flow chart is based upon the one presented by Hägglund (1995), and has been extended to allow the decisions to be influenced by the operational signatures.

Special tests can be costly, both in terms of man hours and in lost production. By focusing attention on the most appropriate test, the operational signatures help reduce these costs. For instance, if the signature suggests a valve non-linearity there is little benefit in retuning the loop. A better strategy would be to examine the valve during a scheduled shut-down and replace it if necessary. Note, however, that if the cost of replacement cannot be justified there are published tuning methods designed to accommodate some valve non-linearities (Piipponen, 1996; McMillan, 1995).

3.2 Application of oscillation diagnosis to refinery control loops

The CLPA index. A low value of the CLPA index indicates a loop that is tuned well. Previous implementation of CLPA in a refinery (Thornhill et

al., 1996) has found a target of $\eta \leq 0.15$ to be suitable.

The CLPA index is a grey signature because a low CLPA value does not always mean that no action is needed. As emphasised by Desborough and Harris (1992) the controller error may have little predictability but the r.m.s. value may still be too high. Therefore, the value of σ_r can be an indicator of a hardware problem. This paper has not examined the value of σ_r , however, because it is a quantity in engineering units. It can only be used effectively in cases where there is an agreed reference with which to compare it. A criterion that σ_r should be no more than 1% of the controller range might be suitable, for example.

Loops having hardware faults - spectral analysis. It is well known that non-linearity in a control loop can give rise to limit cycles (see for example (Cook, 1986)). Limit cycles are periodic, and are usually non-sinusoidal. Harmonics having frequencies at integer multiples of a fundamental frequency appear in the power spectrum if the periodic component is non-sinusoidal. On the other hand, linear control loops generally show no more than one spectral feature or, if they do, the frequencies are not integer multiples. Thus the presence of harmonics in the spectrum is a clear signature of non-linearity.

As shown in Figure 5, the spectra of loops 1 and 2 have harmonics and the diagnosis of non-linearity is readily made in those cases even though the regularity factors for these loops are low. Loop 3 also has harmonics. Loop 5 has poorly resolved peaks in its power spectrum. However, two of the smaller peaks appear at integer multiples of the fundamental and are interpreted as harmonics. Thus loop 5 also has a hardware fault. The reason the harmonics are poorly resolved in this loop is that the oscillatory signal is smaller than the r.m.s. noise, as indicated by a threshold value of only 0.44.

Note that the spectral features in loops 1-3 appear at low frequencies because the periods of oscillation are long. Care must be taken to resolve low-frequency detail by sub-sampling the data set. As a guideline, the fundamental oscillation should be characterised by about 10 to 20 samples after sub-sampling.

Table 2 summarises the above conclusions and puts them with the results from other signatures to make recommendations from the decision-making flow chart in Figure 4.

Loops having hardware faults - sp-pv plots For loops in cascade mode where the set point moves, the presence of non-linear features is also revealed in an sp-pv map. Åström (1991) and McMillan (1995) have illustrated the typical patterns that appear on plots of signal versus stroke for non-linear

Fig 6. Idealised sp - pv maps for dynamic systems

Fig 7. sp and pv plots for loops 2,3, 5 and 7

characteristics such as valve dead band and stick slip. Those illustrations were static plots of the steady-state values, but similar features arise in a dynamic plot of sp versus pv in a closed loop. Figure 6 shows idealised shapes for dynamic sp - pv maps. Note especially that the linear case is not a straight line as it would be in a static plot, because the closed-loop system gives a phase lag to the pv . The plot therefore makes an ellipse on the sp - pv plane.

Information from the sp - pv maps for the refinery loops is entered into Table 2 where it contributes to the decisions. For instance, Figure 7 shows sp - pv maps for loops 2 and 3. Their similarity to the idealised signatures is striking and the classification

is unambiguous. Loop 2 has a dead band, and loop 3 has a valve with stick-slip.

The plot for loop 2 suggests an explanation for the lack of regularity of the oscillations in the master-slave cascade of loops 1 and 2. It is clear that the trajectory usually has small excursions, but sometimes has a large one. Åström (personal communication) has suggested that the dead zone may be larger when the actuator demand signal moves slowly because of a velocity-dependent friction characteristic. Friction behaviour that matches the observation has been reviewed by Olsson (1996) including the finding of Johannes *et al.* (1973) that the break-away force of static friction depends on the rate of application of the tangential force.

The sp - pv map for loop 5 in Figure 7 has some similarity to the idealised map of an oversized valve, but the set point does not move enough to be sure. However, the variability of $\pm 3^\circ$ should alert a refinery control engineer to a problem - temperature control should be tighter than this. Loop 5 is a good illustration of Desborough and Harris's finding that a loop can have a low CLPA index but still be performing poorly because of high residual variability. Loops 1, 6, 8 and 9 have no sp - pv maps because their set points are constant.

Loops with tuning problems. There are few clear indications of a tuning problem because the behaviour of linear, poorly tuned loops can also be seen in loops with non-linearities. One clear signature if the set point moves enough is an elliptical pattern on a sp - pv map. Figure 7 shows that loop 7 has an elliptical pattern in which the major axis is at an angle of greater than 45° (it is a filled-in ellipse because the mean values drift slightly and because of additive noise). It is clear that the loop has a tuning problem. The fact that the amplitude of the pv is larger than the amplitude of the sp means the loop is resonant.

Sinusoidal oscillations are common in over-tuned loops which behave in a resonant manner. A single peak in the power spectrum is therefore taken to be a signature of a tuning problem. The controller error signals for loops 6 and 8 have single spectral peaks (Figure 8). In contrast, the well-tuned loop 9 has a broader and more poorly defined peak. However, tuning problems are not the only cause of a spectral peak, and the signature is therefore a grey one. For instance, the spectrum of a loop with an oscillatory load disturbance may also show a single peak, as shown by Tyler and Morari (1996) in data from the Shell Research Company.

Loop 7 shows evidence of a poorly resolved second peak and it can be seen that the second peak is not a harmonic because the frequencies are not multiples. This loop may be influenced by an oscillatory disturbance.

Fig 8. Power spectra of controller errors for selected loops

Fig 9. Controller error and spectrum for loop 4

Loops with disturbances. The control intention of loop 10, a level control, is to accommodate disturbances to flow by means of a surge in the volume of liquid in the vessel. The time trend (Figure 2) shows two such disturbances.

There are neither harmonics nor a single peak in the spectrum of loop 10, so there are no indications of tuning or hardware problems. It has low regularity and deviations that are large relative to its noise level, and its CLPA index is large.

For a surge-control loop, the response to disturbances is just as planned. However, it illustrates an instance of no indication of either a tuning or a hardware problem for which the advice would usually be towards a special test to confirm that it is influenced by disturbances.

A loop with an unknown problem. Loop 4 has severe oscillations but the cause is not known. The loop appears in the region of Figure 3 that suggests limit cycling due to a hardware fault.

The *sp-pv* map is not available as the set point does not change, and its spectrum appears to show no harmonics. However, a close inspection of the controller error (Figure 9) shows that it is not sinusoidal. It looks like a series of exponential segments from a first-order response to a step. Such a signal can be thought of as a low-pass filtered square wave. Its harmonics should be odd-numbered but of small amplitude. When the spectrum is plotted on a logarithmic scale with 95% confidence limits (Figure 9) it is possible to see that the signal has a third harmonic.

The most likely conclusion about loop 4 is that it has a hardware fault, while the shape of the signal suggests that the non-linearity is of the relay type.

Table 2. Summary of analysis of ten refinery control loops, with decisions

Loop	Clear signatures	Grey indications	Decision
1	Harmonics in spectrum	$\xi > 2/\pi$, $q < 1.3$, $\eta > 0.15$	Static test on flow valve of loop 2
2	Harmonics in spectrum <i>sp-pv</i> map	$\xi > 2/\pi$, $q > 1.3$, $\eta > 0.15$	Static test on flow valve to confirm dead band
3	Harmonics in spectrum <i>sp-pv</i> map	$\xi > 2/\pi$, $q > 1.3$, $\eta > 0.15$	Static test on flow valve to confirm stick-slip
4	Harmonic in spectrum	$\xi > 2/\pi$, $q > 1.3$, $\eta > 0.15$	Static test on hardware
5	Harmonics in spectrum <i>sp-pv</i> map	$\xi > 2/\pi$, $q > 1.3$, $\eta < 0.15$	Oversized valve is already diagnosed. Recommendation is to consider replacing valve at next shut-down.
6	None	$\xi < 2/\pi$, $q > 1.3$, $\eta > 0.15$	Take loop off-line for re-tuning
7	<i>sp-pv</i> map	$\xi < 2/\pi$, $q > 1.3$, $\eta > 0.15$ Secondary spectral peak	Take off-line for re-tuning. Examine possible disturbance by operating in manual or detuned mode
8	None	$\xi < 2/\pi$, $q > 1.3$, $\eta \approx 0.15$ Single peak in spectrum	Take off-line for retuning (NB loop 9 is the retuned loop)
9	None	$\xi < 2/\pi$, $q < 1.3$, $\eta < 0.15$	No action
10	None	$\xi > 2/\pi$, $q < 1.3$, $\eta > 0.15$	Examine possible disturbance by operating in manual or detuned mode

Therefore one has to look carefully at the pressure sensor, the pressure lines and the wiring (Sanders, 1995) on the grounds that these components are more likely to give rapid switching than the actuator. A relay type of non-linearity tends to lead to a high-frequency oscillation as seen in this loop because a relay causes an oscillation at the cross-over frequency (ω_{180}). By contrast, it is known from describing function analysis (see for example, (Anand, 1984)) that a non-linearity with hysteresis such as a valve with a dead band causes oscillations at a much lower frequency than the cross-over frequency.

Decisions. Table 2 summarises the evidence and decisions for each of the ten refinery loops. The evidence reinforces the expert opinions received from the refinery control engineers, except for the following points:

- The procedure found the wrong period of oscillation for the cascade loops 1 and 2. The failure is thought to be due to a lack of regularity and symmetry in the oscillation.
- There is an unexplained spectral feature in loop 7. The loop could be affected by a disturbance.
- Loop 4 has been diagnosed as a hardware fault in the form of a relay-type non-linearity.

Five loops are referred for tests or replacement of hardware, and two for retuning. Loop 9 is confirmed as being well tuned and although loop 8 is slightly oscillatory it is performing well enough to be a low priority. Loop 10 would be referred for disturbance testing were it not for the fact that it was designed to deal with disturbances in the first place.

4. CONCLUSIONS

The work reported in this paper has built on previously published methods for the detection and diagnosis of oscillations. It has introduced new criteria for the detection of oscillations that are especially applicable when the analysis is run off-line. Characterisation of oscillations has been presented in terms of a regularity factor and a threshold that indicates the relative amplitudes of the oscillatory component and signal noise. Signatures based on spectral harmonics and a dynamic map of set point versus process variable have also been introduced.

The procedures make use of measurements from normal process operations, which makes them attractive from a business point of view. In addition, the work has provided a decision chart that makes it clear when and why interventions into normal operations are justified. It focuses on the best type of special test to be done, and on what type of information to seek from the test. The authors believe that such guidance can reduce the hours spent in trouble-shooting, and the amount of lost production.

The routines have been applied to refinery control loops. Analysis and the decisions from the procedures

reinforced the expert opinions of the refinery control engineers in most cases. Cases of disagreement have been fully explained, and the procedure also gave guidance on a loop with an unknown problem.

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