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PERFORMANCE ASSESSMENT AND DIAGNOSIS OF REFINERY CONTROL LOOPS

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Abstract

This paper discusses the application of control loop performance assessment (Desborough and Harris, 1992) in a refinery setting. In a large process it is not feasible to tailor the parameters of the algorithm to every individual control loop. A procedure is illustrated for selecting default values which make it possible to implement the technology on a refinery-wide scale. For instance, it is shown that the prediction horizon parameter in the CLPA algorithm can be set so that the analysis is sensitive to the persistent signals that cause loss of performance. Default values are suggested for refinery applications.

A frequent cause of loss of performance in a control loop is a persistent oscillation due to a valve nonlinearity or a tuning fault. The paper presents an operational signatures in the form of an estimate of the closed loop impulse response that suggest the causes of such oscillations.

Keywords

Control loop performance, refinery control loop, oscillation, signature, valve fault, sampling interval

Introduction

Studies of the performance of single-input-single-output control loops have shown that reasons for poor performance of basic SISO loops 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.

Performance indices have been developed by Harris (1989), Desborough and Harris (1992) and Stanfelj *et al* (1993) which provide figures of merit for the performance of a loop. An advantage of these indices is that they can be derived during normal operations 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) and also in the pulp and paper industry (Perrier and Roche, 1992; Lynch and Dumont, 1996; Jofriet and Bialkowski, 1996; Owen *et al.*, 1996; Harris *et.al*., 1996).

This paper uses the control loop performance assessment technique (CLPA) proposed by Desborough and Harris (1992) for refinery control loops. It addresses some of the challenges laid down by Kozub (1996), in particular the need for an automated on-line system and the determination of dynamic responses. The main aspects of the paper are:

- Default settings for the parameters in the CLPA algorithm that can be used for automated CLPA of all refinery control loops
- A demonstration of how one of the default settings is selected
- Methods to aid engineers in the diagnosis of loops found to be performing poorly.

Key parameters (prediction horizon, sampling interval, data ensemble length, length of the model) are selected as reported by Thornhill *et. al*. (1998). Here, we demonstrate how the prediction horizon parameter in the CLPA algorithm can be set so that the analysis is sensitive to the persistent signals that cause loss of performance. In particular, the results show that the same default settings can be used for all loops of a similar type.

Operational signatures can be found within routine operating data and used for the purposes of diagnosis. 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.

As reported earlier (Thornhill and Hägglund, 1997) the power spectrum helps to distinguish a tuning problem from a limit-cycle oscillation due to non-linearity such as valve friction. New results presented here show that an estimate of the closed loop impulse response also reveals the presence of a limit cycle.

Several authors have reported success in the analysis of disturbances from routine operating data. 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 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. This paper makes use of knowledge of the process flowsheet for a unit in a case where several nearby loops show identical oscillation signatures. The source of the control problem is pinpointed through the use of engineering insight guided by the nature of the signatures.

Methods

Overview

The key variable for CLPA is the controller error, *e*, given by (*sp-pv*). If the loop is performing well it should reject disturbances, and the process variable should track the set point. These requirements imply that the controller error should have no predictable component. There should not, for example, be a steady state offset or any persistent oscillation.

Because of the dynamic nature of the process and of the controller itself it takes a little time for the controller to achieve rejection of a disturbance or to bring the process to its set point. Thus the intent of the performance index is to determine how predictable the controller error is beyond some suitable time horizon. If the control error is predictable over this time horizon then the loop is performing poorly and, by contrast, it is performing well if the error is unpredictable over this time horizon.

Theory

Desborough and Harris (1992) devised an index based upon the residuals between the measured controller error denoted by Y and a forward prediction, $\hat{y}$.

$$r(n) = Y(n) - \hat{y}(n) \qquad [1]$$

In a loop that is performing well the controller error has little predictability and the controller error contains only the random noise represented by the residuals. But in a poorly performing loop, one with a significant predictable component, the random residuals are much smaller than the controller error.

Desborough and Harris proposed the following CLPA index. A poorly performing loop has a value of η close to 1 while η for a good loop is close to 0:

$$\eta = 1 - \frac{\sigma^2{}_r}{mse(Y_i^2)}$$

$\sigma^2{}_r$: variance of the residuals
$mse(Y_i^2)$: mean square value of controller error

The requirement for the prediction model for $\hat{y}$ is just that it is capable of capturing features in the controller error sequence. Desborough and Harris (1992) show that for typical data from process control loops an autoregressive time series model that makes predictions *b* steps ahead is suitable:

$$\hat{y}(i+b) = a(0) + a(1)Y(i) + a(2)Y(i-1) + \ldots + a(m)Y(i-m+1) \qquad [2]$$

The above model is fitted to an ensemble of n samples of the controller error using a least squares fit procedure.

Strategy for application to a large plant.

In a refinery there are large numbers of basic SISO feedback loops. An automated CLPA technique needs a means of providing suitable models for every loop. The autoregressive model needs certain parameters to be specified. These are:

The prediction horizon, *b*
The number of terms in the model, *m*
The sampling interval
The data ensemble length

It is important to realise that the sampling interval is much longer that the sample interval used in the on-line PID control algorithm. The issue is to capture the closed loop transient dynamics of the process within the time interval spanned by the m terms of the autoregressive model. The proposed strategy for making these choices for a large scale implementation relies upon a classification of control loops into a few generic types. Examples in a refinery would include liquid flow, steam flow, temperature and pressure loops. It is argued (Thornhill *et. al*., 1998) that the CLPA parameters optimised for a few representative examples of loops of one type can be applied to *all* loops of that type. Such a strategy covers most cases thus allows automated on-line monitoring. The recommended choices for the parameters are given below.

Loop type	*Sampling interval*	*Prediction horizon, b*
Pressure	*20s*	*100s*
Liquid flow	*6s*	*30s*
Temperature	*60-120s*	*360s - 600s*
Steam or gas flow	*60s*	*300s*
Level	*20s*	*100s*
Ensemble length	*500-1500 samples*	
Length of AR model, m	*30 terms*	

Choice of prediction horizon

The recommended settings for the prediction horizon, *b*, were arrived at using the method briefly outlined here and which is illustrated in the results section.

Exploration of the effects of different choices of prediction horizon on a selection of representative loops gives an insight into a suitable horizon. In this approach the prediction horizon is regarded as an *engineering criterion*, representing a demand made by the control engineer on the control loop; the criterion is that predictable components of the controller error should be dealt with within the specified time horizon.

CLPA signatures

Desborough and Harris (1992) indicated the value of the power spectral density of the controller error.

In our work we have used power spectra of the controller error in order to provide an insight into the nature of a problem. The power spectra are computed by the Welch method (Welch, 1967) from a windowed fast Fourier transform

An additional signature is also presented, that of the cross-correlation of the modelling residuals from [1] and the controller errors, *Y*. The following comments give an insight into this cross-correlation as an estimate of the closed loop impulse response (Tyler and Morari, 1996)

As mentioned, the controller error sequence is modelled as an autoregressive sequence [2]. However, other time series models also suffice, for example, a model of the following form could be used:

$$Y(n) = c(0)u(n) + c(1)u(n-1) + \dots \qquad [3]$$

where the inputs $u(n)$ form a white noise sequence and the coefficients $c(n)$ form the impulse response of the closed loop transfer from the $u(n)$ to the controller error. It is well known that the cross-correlation function of the $u(n)$ and $Y(n)$ sequences gives the coefficients of the impulse response.

For the purposes of closed loop identification the residuals $r(n)$ are identified with the $u(n)$ sequence for the model in equation [3]. For a practical control loop the noise does not usually enter the loop at the set point; it is more often process noise or due to disturbances. However, if the use of the estimated impulse response is restricted to determination of the natural frequency and damping factor the approximations are acceptable because the damping factor and natural frequency are characteristic of the dominant closed loop poles which can be excited by an input at any point in the loop.

Oscillation detection

Oscillation diagnosis can guide a process control engineer towards suitable special off-line tests. Hägglund (1995) and Thornhill and Hägglund (1997) presented techniques for the characterisation of oscillation in control loops and gave flow charts for diagnosis of the likely cause of an oscillation. They include:

- Interpretation of the CLPA index, a regularity factor and oscillation-detection threshold.
- Examination of features in the power spectrum of the controller error.
- Dynamic *sp-pv* maps for loops where the set point changes often, such as loops in cascade mode.

The following conclusions can follow from the operational signatures

- 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 there may be a disturbance.

This paper presents a further analysis of an example studied in the previous paper by showing how an estimate of the impulse response gives confirmation of a limit cycle caused by a valve fault. It also presents a new case that illustrates the last item on the above list, that of a disturbance.

The issue of automation has not been addressed for the diagnosis step of CLPA. It is supposed that an automated monitoring system will highlight loops with problems, but that process control engineers will want to look at such loops themselves. Tools such as spectral analysis and estimated impulse responses provide meaningful signatures; they also begin to address the call by Kozub (1996) for determination of dynamic responses.

Refinery examples

Several loops from refineries in Australia, the UK and USA were used to in the selection of prediction horizons. In addition, some loops are inspected in more detail:

Loops 1 to 3: A liquid flow loop having different PID tuning settings. Loop 1 is when the loop is underdamped, Loop 2 has more damping and Loop 3 is over-damped.

Loops 4 and 5: Liquid flow loops known to have, respectively, valve stick slip and a valve dead-band.

Loops 6 to 8: Steam flow loop (Loop 8) which is the slave in a cascade temperature control loop (Loop 7). Loop 6 is an on-line analyser at the top of the column (Fig. 4).

Results

Examples of prediction horizon calculations

Figure 1 shows a set of prediction horizon plots to illustrate the selection of refinery-wide CLPA settings. All the plots show a similar pattern, the key feature of which is the plateau where the CLPA index is constant over a range of values of the prediction horizon.

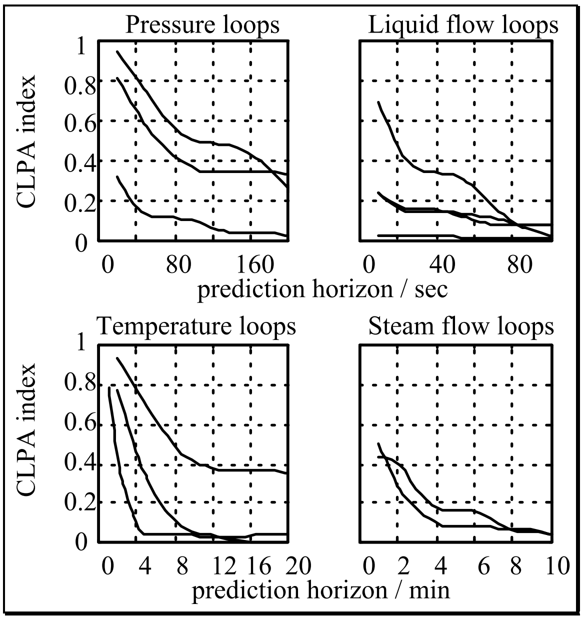

Figure 1. Prediction horizon plots for a selection of typical refinery control loops.

The significance of the plateau is that the controller error contains a component that is predictable a considerable time ahead. Such predictable components are the cause of concern. Thus Fig. 1 suggests, for instance, that the CLPA prediction horizon parameter should be set to 30s for all refinery liquid flow loops and 5 minutes for refinery steam flow loops.

These prediction horizon plots give an independent means for selection of the sample interval. The decision has been made to use 30 terms in the autoregression, which implies that the impulse response is to be captured within that time span, say in 20 to 30 samples. The settling time of the impulse response is four time constants, τ. Thus $\tau = 5 - 7.5$ sample intervals. But for a well tuned controller with, say, a damping factor of $\zeta > 0.6$ one would not expect significant coherence in the controller error at times beyond τ (this assertion is related to the bandwidth of the closed loop resonance in the frequency domain). Hence the sampling interval should be chosen so that the prediction horizon represents about 5 to 7.5 sampling intervals. It is concluded, for example, that for liquid flow loops a sampling interval of 6s would be suitable and for steam flow loops, it would be 1min.

Estimated impulse responses

Figure 2 shows estimated impulse responses for Loops 1 to 3 made from routine operating data. It was indicated earlier that the estimated impulse responses are able to give good indications of natural frequency and damping factor. The damping factors can be estimated from the first peak of the response (Thaler, 1989) as $\zeta = 0.5$ for Loop 1, $\zeta \approx 0.7$ for Loop 2 and $\zeta > 1.0$ for Loop 3.

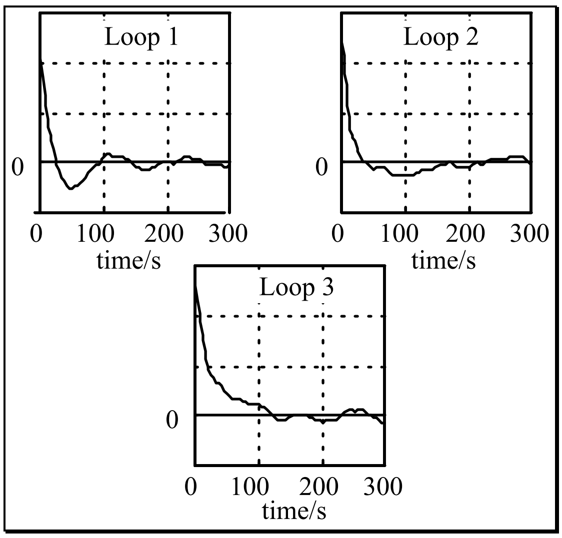

Figure 2. Estimated impulse responses for one liquid flow loop with different tuning settings.

The true impulse response would be expected to die away to zero as the loop settles but the estimated impulse responses do not always have this ideal behaviour. Loops 1 to 3 exhibit a series of small amplitude, random deviations after settling which are within the confidence limits for the estimate. These, therefore are of no importance. For loops 4 and 5 (Fig. 3) however, the long term deviations are regular and large. These loops are known to exhibit limit cycles caused by valve non-linearity. A practical impulse response test on the loop would be expected to initiate the limit cycle, and this is exactly what the impulse response estimation algorithm shows. It is concluded that the presence over a long time scale of a persistent repeating pattern in the estimated impulse response gives an additional diagnostic signature for a nonlinear limit cycle.

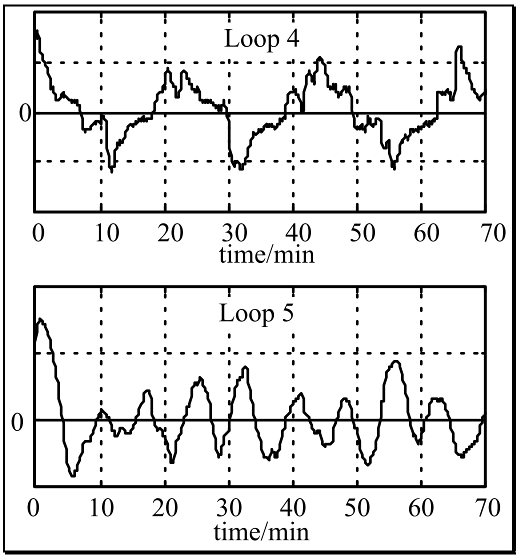

Figure 3. Estimated impulse responses for two liquid flow loops with limit cycles.

Tracking of a disturbance

Figure 4 shows a schematic of a refinery unit in which the CLPA assessment indicated that several control loops had poor performance.

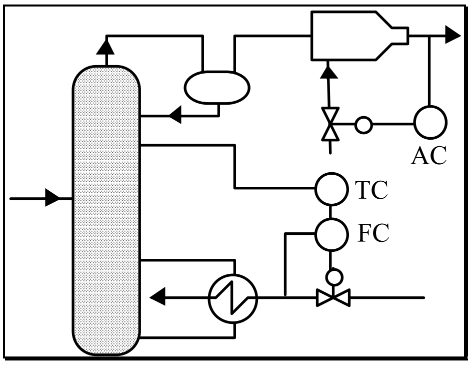

Figure 4. Schematic of a process unit. The three control loops show similar persistent oscillations.

Figure 5 shows signatures for the spectra and long term estimated impulse responses for three loops. (A good way to present this information in a refinery in order to gain process insight is to fix the process flow sheet to the wall and to pin print-outs of the oscillation signatures at the relevant sensors on the flow sheet).

The main features of the spectra are that they all have a sharp spectral peak at exactly the same frequency, $f = 2.5 \times 10^{-3}\,Hz$ (i.e. oscillations having a period of 400s). The estimated impulse responses have the same oscillation period as indicated in the spectra (400s or 6.7 min). The spectral features at very low frequency in Loops 6 and 7 are due to the fact that these process variables exhibit also some long term offsets from the set point.

It is thought that the column-wide oscillatory disturbance is caused by a faulty steam flow sensor in the flow loop. The spectral signature for the steam flow loop shows a harmonic peak which is double the frequency of the fundamental, a clear indication of a non-linearity (Thornhill and Hägglund, 1997). If the flow loop were limit cycling then it might be expected that it will disturb the whole column and that the oscillation will appear at the other sensors. The reason why the second spectral peak is not present at the other sensors is thought to be that the column acts as a mechanical low-pass system and filters out the higher frequency.

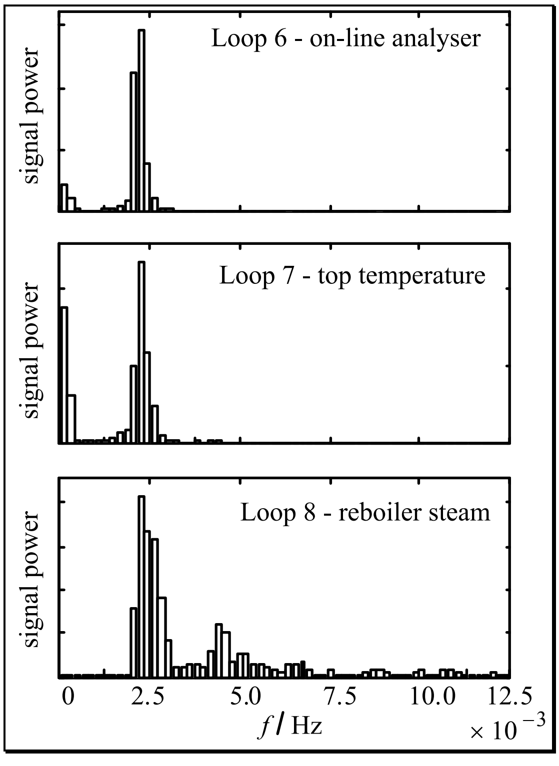

Figure 5. Power spectra for the three control loops of Fig 4 that have related persistent oscillations.

This example leads to the conclusion that the use of the spectral and impulse response signatures can help in the analysis of control system disturbances.

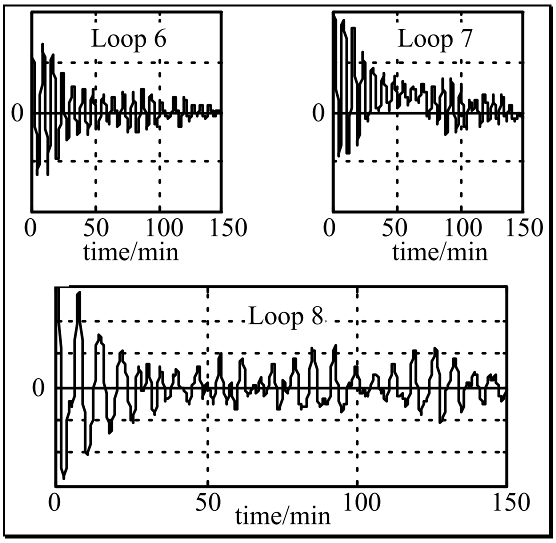

Figure 6. Estimated impulse responses for the three control loops of Fig. 4.

Conclusions

The detailed conclusions that can be drawn from the results have been highlighted at the end of each sub-section. The paper has started to address the challenges laid down by Kozub (1996). For instance, it has shown that it is feasible to implement automated CLPA in a refinery setting. It has also illustrated that an estimate of the closed loop impulse response gives information about closed loop dynamics, where the estimate uses only data from routine process operations without the need for special tests. The impulse response signature can be used to determine damping factor and can also indicate when a control loop oscillation is due to a limit cycle.

Refinery-wide automated on-line CLPA *monitoring* has been achieved through the use of default settings for the CLPA algorithm of Desborough and Harris (1992). The *diagnosis* of loops found to be performing poorly is not automated, however. The CLPA signatures combined with insight from engineers about their interpretation and the process layout are of value in suggesting testable hypotheses about the causes of poor performance.

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