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CONTROLLER PERFORMANCE MONITORING AND DIAGNOSIS. INDUSTRIAL PERSPECTIVE

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Controller performance monitoring and diagnosis is beneficial to ensure profitable implementation of control in practice. The goal of this paper is share the experience of the author with respect to useful technology that has been developed in this field. Particular attention is given to the problem of monitoring industrial multivariable controllers. Industrial examples and opportunities for further research are presented.

Keywords: Monitoring Feed Back Loops; Closed Loop Control; Control Analysis

1. INTRODUCTION

Automated process control (APC) has long been recognized as beneficial for improved process operation. With the increased penetration of process control technology in recent decades it has become evident that the realization of APC benefits require that routine monitoring and maintenance be carried out both effectively and efficiently. The reasons include incorrect a priori design assumptions, changing (time variant) process operating conditions, process nonlinearities, and changes/problems associated with instrumentation and equipment.

The last decade has seen significant attention devoted to this topic by both the academic and industrial communities. Evidence of this was shown at the Chemical Process Control 6 Conference (CPC 6) (Tucson, 2001) where an entire session was devoted to the topic of controller performance monitoring. Readers interested in an excellent source of review material are asked to refer to these papers (Harris and Seppala, 2001; Desborough and Miller, 2001; Shah et al, 2001). The purpose of this paper is to provide feedback on some of the relevant work that we have found useful in our business practice. Some discussion will be provided on the state of monitoring with respect to single input / single output (SISO) control (e.g. base level). Particular attention will be given to the problem of monitoring optimizing multivariable controllers. Examples will be demonstrated with data from industrial applications. It will be shown that, despite recent significant advances, there still exists research opportunities for improved technology for controller monitoring and diagnosis in practice. This is especially true for the optimizing multivariable controller problem.

2. UPTIME

Historically, loop uptime, or in service factor, has been the most frequently utilized statistic for monitoring the performance of control systems. Uptime reporting makes minimal use of available process data. It can be viewed as the extreme form of data compression with respect to controller performance monitoring. Only the state of the controller (On/Off) is used to calculate the statistic. Nevertheless, this first, low level information is essential in any effective controller monitoring strategy. Loops with low uptimes are usually given higher priority with respect to maintenance work. The most frequent causes of low loop uptime are often associated with instrumentation, actuator, and process equipment problems.

While controller uptime information can always be considered essential for monitoring performance, experience has shown that this information alone is not sufficient to ensure optimal performance. Loops operating at uptimes greater than 95 % are often encountered which yield stable, but poor dynamic response characteristics. Miller and Desborough (2001) carried out a comprehensive audit of thousands of industrial base level control loops. Their results led to the conclusion that, despite high uptime, there was a significant opportunity for improved performance with a large percentage of loops investigated. Another issue that poses problems with uptime reporting is the lack of consistency with its calculation. This is especially true for the multivariable case. In this case, some weighted average of CV and MV uptime is used. In extreme cases, uptime is reported based on the controller being on, with complete disregard for the number of inactive CVs and MVs.

The discussion that follows will be concerned with statistical information that will serve to compliment the limited information provided by controller uptime.

3. SINGLE CV/MV CONTROL

3.1 Preliminaries

The single input / single output (SISO) controller problem has been the most thoroughly investigated case, and where most of the applications experience lies. The unconstrained, SISO case can be described by

$$y_t = P(z^{-1})u_t + \sum_i D_i(z^{-1})d_{i,t} + \nu_t \quad (1)$$

$$u_t = C(z^{-1})e_t + \sum_i C_{f,i}(z^{-1})d_{i,t} \quad (2)$$

$$e_t = s_t - y_t \quad (3)$$

where, at sampling interval t, y_t is the control output (CV), u_t is the manipulated control input (MV), $d_{i,t}$ is an i'th measurable disturbance, υ_t represents the net additive effect of noise and unmeasured disturbances on the CV, s_t is the CV set point, and e_t is the controller error from set point. $P(z^{-1})$, $C(z^{-1})$, $D_i(z^{-1})$, and $C_{f,i}(z^{-1})$ are the discrete time transfer functions representing the effect of u_t, e_t, and $d_{i,t}$ on either the CV or MV response. Using these equations, The closed loop CV error from set point and MV response will be

$$e_t = s_t - y_t = \frac{s_t - \sum_i \left(P(z^{-1})C_{f,i}(z^{-1}) + D_i(z^{-1})\right)d_{i,t} - v_t}{1 + P(z^{-1})C(z^{-1})} \quad (4)$$

$$u_t = C(z^{-1})e_t \quad (5)$$

For the purpose of SISO controller performance monitoring and diagnosis, the dynamic response characteristics associated with (4) and (5) are of concern.

3.2 ARMA Time Series Modelling

The net dynamic response associated with e_t can be described by an Auto-Regressive, Moving Average (ARMA) time series model of the form

$$e_t = \frac{\theta(z^{-1})}{\phi(z^{-1})}a_t = (1 + \psi_1 z^{-1} + \psi_2 z^{-2} + \cdots)a_t \quad (6)$$

where a_t is a white noise time series model arising from any zero mean distribution. These models can be easily identified from process response data using minimum variance, prediction error criteria (Box and Jenkins, 1976). A similar time series model can be identified for u_t, or measured loop disturbances. The impulse response for (6) provides some average e_t response for the data window of observation. The dynamic characteristics of the estimated models are determined by the trend features that contribute most to the variance of the trend. As can be observed from (4) and (5), the estimated ARMA model properties will be determined by both the relative magnitudes and dynamic features of υ_t, s_t and $d_{i,t}$'s in the window of observation, and transfer functions $P(z^{-1})$, $C(z^{-1})$, $D_i(z^{-1})$, and $C_{f,i}(z^{-1})$.

ARMA model average response estimation has been found useful in practice. It is now reaching the point of widespread use, particularly with respect to SISO base level applications. Our experiences have led us to conclude the following:

- Average response modelling greatly facilitates the task of loop monitoring and auditing. Performance can be easily accessed in a very short time span with software that automates model estimation and provides the results in a user-friendly fashion. We have seen a tremendous reduction in manpower effort relative to the sole use of visual trend analysis and intrusive procedures.
- Relative to auto-correlation and spectral analyses, ARMA average response modelling has been considered far more straightforward to use. The former procedures, while providing similar information, have been considered far more challenging to interpret by control engineers in the chemical engineering field.
- Performance information that was not readily apparent has been exposed with theses analyses. Hence, significant opportunities for performance improvement were identified. It has also been helpful in arriving at optimal loop tuning.
- The success of using this method in practice requires a critical threshold of training. It does not replace process know how or use of trend data. It compliments this information. The results of the analyses are a function of data chosen. Hence, the data must be informative, requiring good judgement on the part of control engineers carrying out the analysis. The results can also be a challenge to interpret when significant multiple disturbance sources are present, and when time variant conditions prevail. Nevertheless, our experience has been that the information provided is beneficial relative to its limitations and initial training hurdles.

3.3 Minimum Variance Estimation

Historically, standard deviation monitoring of CV error from set point has often been carried out, and found useful. From the perspective of controller performance monitoring, experience has shown this information can be both limited and misleading. Set point error standard deviation is a function of the magnitude of loop upsets. Changes in this statistical information can be a function of changing process conditions, and may not necessarily reflect performance of a controller. During periods of large plant upsets, higher standard deviations are to be expected despite the fact that controllers are responding as designed. During calm periods of operation, low standard deviations can be observed with poorly design controllers.

Harris (1989) showed that the lowest achievable variance under feedback control, referred to as the condition of Minimum Variance Feedback Control (MVC), can be easily estimated by fitting an ARMA time series model to e_t data. Relative to (6), the estimated MVC response is given by

$$e_{MVC,t} = (1 + \psi_1 z^{-1} + \psi_2 z^{-2} + \cdots + \psi_{k-1} z^{-k+1})a_t \quad (7)$$

$$\sigma^2_{MVC} = (1 + \psi_1^2 + \psi_2^2 + \cdots + \psi_{k-1}^2)\sigma_a^2 \quad (8)$$

where k is the whole number of sample periods of continuous time delay, $e_{MVC,t}$ is the estimated MVC response, and σ^2_{mvc} is the estimated MVC closed loop variance for the data window of observation. By making use of σ^2_{mvc}, the estimated error from set point standard deviation can be compared to this theoretically lower bound that will change according different process/disturbance conditions. This relative comparison of statistics can be viewed as normalization in some sense with respect to controller performance. This has lead to the introduction of various variance ratio statistics that have been advocated for performance monitoring (see references).

There has been considerable hoopla, particularly by academics, concerning the usefulness of MVC with respect to monitoring controllers. Relative MVC standard deviation/variance monitoring is hardly as informative as the information provided by more detailed ARMA average response curves. Our experiences with this type of analysis are listed below.

- The MVC lower bound can be useful for separating control related problems from process ones. Situations arise when problems external to a particular control loop are yielding higher variation than can be accepted (e.g. upstream disturbances). Higher variation without accompanying poor relative MVC performance strongly indicates that root cause corrections should investigated external to the control loop.
- Automation of the MVC assessment, along with other statistical information, can serve as a first pass-monitoring layer to bring obvious problems to immediate attention. By itself, it does not provide sufficient useful information.
- The MVC lower bound can assist in setting reasonable performance targets. Specification of overly optimistic and conservative performance targets can be avoided with this information. MVC information can also be beneficial in incentive studies.

3.4 SISO Example

To illustrate the application of these concepts consider some data collected from an industrial SISO base level controller as shown in Figure 1. The top plot shows the CV trend (black) and its set point that is fixed at a constant value. The second plot shows the MV trend. Since the set point is constant, the goal will be to evaluate controller disturbance regulation in the data time range. The significant drifting MV trend indicates that disturbances are present. The third plot shows sliding window calculations of CV error from set point (black) and the MVC estimated standard deviations (grey). The width of the bars indicates the time span of the sliding windows used to carry out the standard deviation calculations. The dashed line in this plot shows the required upper bound limit for the CV error from set point that must be met. The localised, windowed standard deviation statistics indicates that performance throughout the entire data range appears to been consistent. The relative ratios of the MVC to CV error from set point standard deviation bars indicate performance not far from minimum variance feedback. However, the standard deviation performance specification is not being met. The results shown in the third plot clearly indicate that the performance specification would not have been met even if the tightest possible, minimum variance feedback control were applied.

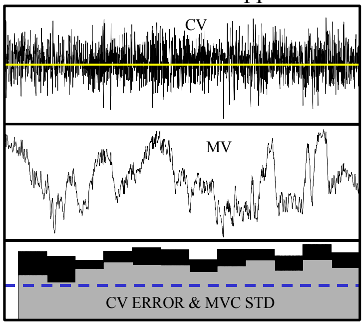

Fig. 1. SISO Loop Response
a) CV/Set Point Trend; b) MV trend;
c) CV error & MVC standard Deviations

More insight can be gained by looking at the average response curves for both the CV error response (top) and MV trend (bottom), as shown in Figure 2.

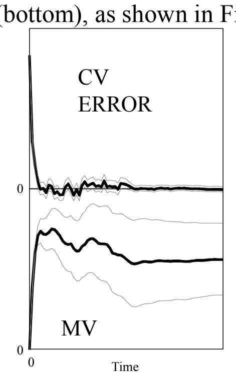

Fig. 2. Average Responses
a) CV Error From Set Point; b) MV trend

The estimated average response curves were generated by fitting ARMA models to the entire data set. In Figure 2, the black curves indicate the estimated average response trends while the grey lines provide a 95% confidence interval. The rapid decay of the CV error relative to the time scale of concern clearly indicates tight control. For this process, there is no MV/CV deadtime. Hence, the absence of MVC control from the information in Figure 1 is confirmed by the average response analysis since CV error does not decay to zero at the first sampling interval. However, the response is not far from this condition. The MV average response can be observed to be very good. The MV rises rapidly close to its final steady value with only a slight amount of overshoot.

These analyses lead to the conclusion that the performance of the controller is good. The problem with the performance specification not being met cannot be addressed by a better feedback controller. Disturbance variance reduction at the source in this case needs to be investigated. This conclusion would not be easily arrived at without the analyses carried out.

3.5 Closed Loop System Identification

While ARMA time series modelling has been proven useful in practice, the information it provides can be limited because the contributing effects of all loop disturbances and set points become confounded. Kozub (1996) advocated the use of closed loop identification to take advantage of measured loop disturbances to identify models of the form:

$$e_t = S(z^{-1})s_t + \sum_i \Delta(z^{-1})d_{i,t} + \frac{\theta(z^{-1})}{\phi(z^{-1})}a_t \quad (9)$$

The interpretation of each of these transfer functions can be easily arrived at by comparing (9) with (4). Equation (9) can be used to provide predicted average responses to individual, measured contributions, as well as the residual unmeasurable disturbance/noise contribution. This information can provide far more insight about the performance properties of a controller. Refer to Kozub(1996) for an example application to industrial data. Closed loop identification has been proven useful to us, and the concept extends easily to multivariable problems. The lack of more reported use of closed loop identification remains a mystery to this author.

4. MULTIVARIABLE CONTROL

The state of research and applications experience in the area of multivariable controller performance monitoring is much less evolved compared to the SISO case. In this section, some opinions/feedback will be offered on this subject based on our experiences.

4.1 MIMO Extension of MVC

While the concept of MVC is straightforward in the SISO problem, the multivariable extension is far more challenging from both a theoretical and applications viewpoint. Huang and Shah (1999) have advocated the use of a weighted output error variance metric for MVC estimation since it is closely related to the cost function employed in multivariate, unconstrained linear quadratic controller designs. The solution for this case is non-trivial, and requires the estimation of a unitary interactor polynomial matrix from the matrix transfer function, and the solution of a polynomial, multivariate diophantine equation. Readers interested in the details are asked to refer to the cited reference.

For the multivariable case, the use of a weighed LQ MVC measure is somewhat controversial, and has not been widely applied for various reasons. Some of the issues are listed below:

- Significant process transfer function information, other than deadtime alone, is needed relative to the univariate case. The integrity of the MVC calculation in the presence of modeling error is unknown.
- The output weighted, linear quadratic cost function is often viewed as a convenient mathematical formulation to arrive at some analytical solution for a feedback controller. Hence, the output LQ weights are often tuning weights that don't truly reflect relative performance in practice. One important practical concern with respect to online implementation is that these weights can change significantly, depending on where CVs and MVs are positioned relative to constraint limits. This makes the computation of MVC more of challenge to carry out because of time variant weighting changes.
- Most industrial multivariable controllers are non-square, finite horizon, constrained model predictive controllers with simultaneous optimization carried out with the steady state gains. The optimization problem is typically solved using a linear program(LP). Although these controllers have some features in common with L.Q. control, important significant differences must be taken into account when monitoring these applications. This will be illustrated in an example that will follow bellow.
- At this time, there is an absence of readily available, quality/friendly code for out carrying out the advanced MIMO MVC calculations. Adequate software is needed for practitioners to get a better feel for the value of the analysis on commercial applications.

4.2 MIMO Times Series Average Response

The SISO idea of fitting CV error trend data to time series models for the purpose generating average response information has been extended to the multivariable/multi-loop problem. Harris & Seppala (2001) discuss the use of vector auto-regressive (VAR) time series models of the form

$$\Phi(z^{-1})e_t = a_t \quad (10)$$

where e_t is the error from set point vector, a_t is a zero mean white noise vector, and $\Phi(z^{-1})$ is an auto-regressive, full matrix polynomial. For multivariate and multi-loop systems, impulse response analysis can potentially provide valuable information related to multivariate interactions and propagation of the disturbances relative to their effect on the outputs. An application of VAR to industrial data is shown by Harris & Seppala (2001) where the usefulness of this analysis is demonstrated. While limited work and experience has been carried out with VAR, and closely related approaches (e.g. subspace), it is the opinion of this author that this approach is useful for continued research and evaluation.

4.3 Example MPC Control

To exemplify some of the issues related to multivariable controller monitoring, consider some data acquired from a commercially available MPC controller. The characteristics of this controller are:

number of CVs is 18; number of MVs is 10; and the number of feedforward disturbances is 4. As far as industrial multivariable controllers are concerned in the petrochemical industries, this controller can be considered small. Nevertheless, for the purpose of this paper, it is sufficient for illustrating some important points. The CV versus MV step response model used by the controller is shown in Figure 3. Blacked out boxes indicate a zero CV/MV response. The time span is 90 minutes for the responses. As can be seen in the Figure, the multivariate model is sparse, which tends to be common with most of these applications. Similar step response models for the CV/feedforward responses were employed by the controller.

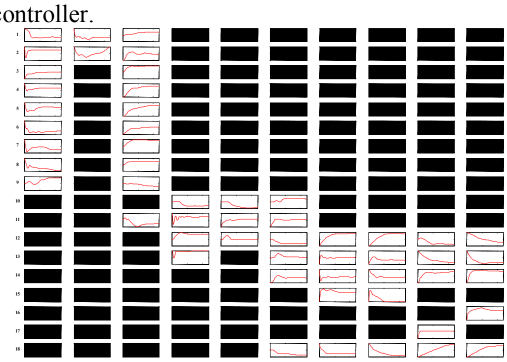

Fig. 3. CV versus MV Step Response Models

The MPC controller has both a steady state LP optimization layer and a multivariable feedback control layer that operates at the same execution rate. The LP utilizes the gains from the step response model with LP cost factors specified. High and low limit constraints for all CVs and MVs are specified, and can be adjusted during operation. The feedback controller is an unconstrained MPC formulation. Hence, constraints are dealt with at the projected steady state by the LP that passes targets to the feedback controller. Approximately, two weeks of data were collected for this application. The data was considered representative of routine operation.

Figure 4 provides information on the % time that each CV (top) is being driven to a constraint. The bottom plot show the % time that each MV is not set to a constraint, and therefore, available for feedback. From the CV information, it is apparent that only 5 to 6 CVs are driven to LP limits by the controller. The remaining CVs float between high and low LP limits. From a feedback controller standpoint, a CV driven to an LP limit can be considered to have a set point during these periods as specified by the constraint bound. The CVs at LP limits are intuitively more important from a monitoring perspective relative to CVs which are floating within constraint bounds. During floating periods, we have found from experience, that the associated LP targets tend to follow/track the CVs within bounds. These CVs are often assigned 0 (or near 0) weighting in the feedback controller which essentially puts them into an open loop state. Furthermore, the L.P. targets tend to be noisier relative to their CVs due to the inherent poor steady state projections. Hence, from a monitoring viewpoint, error from LP target during these periods is essentially meaningless, or relatively unimportant. Nevertheless, CVs trends that erratically change between floating and LP limit states are a characteristic that is important to detected and monitor. From the MV bar plot (bottom) in Figure 4 it can be observed that 4 to 5 MVs appear to be significantly free from constraints for feedback control. The remaining MVs appear to be fixed at LP constraint limits, and therefore, remain at an open loop state.

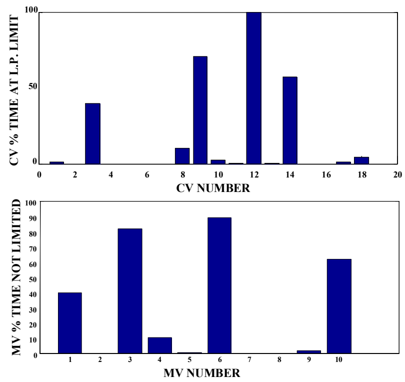

Fig. 4. % Constraint Activity:
a) % CV Time at L.P. Limit
b) % MV Time not at L.P. Limit

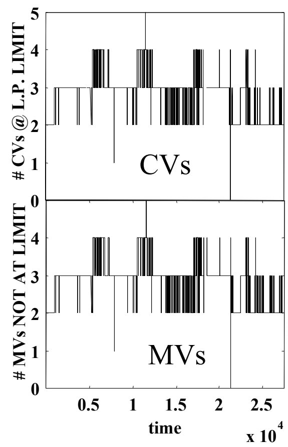

Fig. 5. Dynamic Constraint Activity Trends
a) Number CVs Time at L.P. Limit Trend
b) Number MVs not at L.P. Limit Trend

Figure 5 provides additional insight into the performance of the controller LP layer. The top plot shows the number of CVs being driven to an LP bound as a function of time. The bottom plot shows the number of MVs free for feedback control (not at limit) as a function of time. This information shows how the LP is driving the dimension of feedback control as a function of time. The dimensionality can be observed to be swapping from mainly 2, 3, and 5, with 3 being the most frequent case (3 by 3 control). The figure also reveals that considerable chattering is occurring with respect to the controller dimension. Based on experience, this can be a cause for concern because often the economics/plant conditions are not expected to change at such a rapid time scale. Overall, these two simple-minded plots have indicated that there may be LP stability problems. Furthermore, the dimension of the controller seems to vary mainly between 2 to 4, involving mostly 6 and 5 CVs and MVs respectively. If the data is truly representative, the implication of this observation is that there might be an opportunity to prune the controller size, which would yield a smaller, simpler controller to maintain. The information is also helpful for prioritizing CVs and MVs for monitoring analysis.

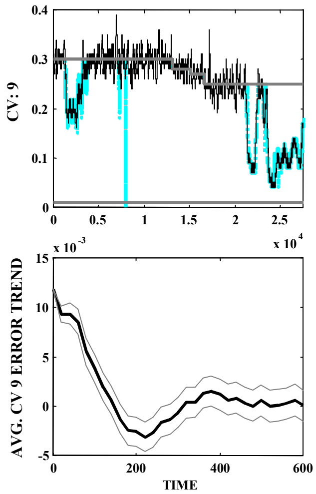

Fig. 6. CV number 9: a) Trend Plot; b) Average CV Error Response (LP bound only)

Figure 6 (top) shows trend information associated with CV 9 in the controller. The CV trend is indicated in black. The LP high and low limits are indicated in gray. The LP target is shown by the (--) trend. This CV is the second most frequent CV (see Figure 4) that rides LP limits. Using only data when the LP target (set point) is at a bound the average error response, as discussed in section 3.2, can be estimated. This is shown in the bottom plot in Figure 6. The performance of the controller in holding the CV at the upper target can be observed to be poor. The settling time is about 400 minutes, which is very sluggish relative to the 90-minute open loop step response models. As discussed earlier, inclusion of the data during CV floating target periods yields misleading information. A similar dynamic response analysis can be carried out on the remaining 5 CVs that spend significant time being driven to LP bounds. Based on our experiences, this analysis has proven to be very useful, provided the state of the CV with respect to the LP is accounted for.

The results from this relatively simple example serve to show that the scope of MIMO controller monitoring is far more involved relative to the SISO case. Some important issues for the reader to appreciate are:

- The amount of the data that needs to analyzed and interpreted accurately is nontrivial.
- The LP layer, being integrated with the feedback controller, cannot be ignored when carrying out monitoring analysis. Both its dynamic properties and effect on the feedback layer must be examined.
- Models are always available for analysis. Although this issue was not discussed here, it would be highly beneficial to make effective use of this information.
- Some of the univariate concepts have been shown to extend to these problems, However, issues, such as MIMO MVC need to be reconsidered relative to the framework of commercial MPC in order to be proven useful.

It is the opinion of the author that far more research is needed to find effective solutions to MIMO controller monitoring. The role of MIMO performance is felt to be important to the future of MPC control. The optimization formulation and size of these controllers in practice has been somewhat controversial in the MPC community. Quantitative monitoring has the potential of providing some important insight in addressing these issues.

5. CLOSING REMARKS

Controller performance monitoring is important to ensure the success of process control technology. The information presented in this paper has shown that useful technology has been proposed that is now becoming adopted in practice. While the significant progress has been made with univariate (base level) control, far more challenging research opportunities still remain to address the practical issues concerned with industrial multivariable control.

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