MULTIVARIABLE CONTROLLER PERFORMANCE MONITORING

S. Joe Qin [1] and **Jie Yu**

Department of Chemical Engineering
The University of Texas at Austin
Austin, TX 78712, USA

Abstract: In this paper we give a critical overview of recent development in MIMO control performance monitoring. We discuss a number of MIMO control benchmarks including minimum variance, LQG, and user selected benchmarks. Performance measures are extended from variance based measures in SISO control to covariance based measures in MIMO control. Pros and cons of various benchmarks are discussed. The diagnosis of poor control performance relative to a benchmark is a major focus of the paper. We argue that in the MIMO setting worst performance directions should be analyzed from data to yield meaningful diagnosis information. Therefore, multivariate statistics should be applied for the diagnosis of worst performance directions, much like its use in multivariate process monitoring.

Keywords:
MIMO control performance monitoring, minimum variance, model predictive control, covariance based monitoring, worst performance directions.

1. INTRODUCTION

Control performance monitoring and evaluation can be traced to Åström (Åström, 1970; Åström, 1976) and later Harris (Harris, 1989) who demonstrated that the minimum variance benchmark can be estimated from normal closed-loop operation data. Åström in his CPC-2 paper (Åström, 1976) noted the following:

> In the special case of minimum variance control ... it is known that the covariance function will vanish for lags greater than the sum of the sampling interval and transport delay of the system. It is then sufficient to record output only and to compute its covariance function.

The interest from both academia and industry in control performance monitoring has surged tremendously in the last decade as documented in several review papers and a monograph (Qin, 1998; Harris *et al.*, 1999; Kozub, 1996; Harris and Seppala, 2002; Hoo *et al.*, 2003; Huang and Shah, 1999). The recent survey paper by Jelali (Jelali, 2006) provides a very good collection of recent development in the control performance monitoring area from SISO, MIMO to valve stiction problems. In the application domain, just in HVAC systems alone, Johnson Control has implemented over half a million control monitors in the last ten years based on a pattern recognition technique (Seem, 1998; Seem, 2006). Paulonis and Cox (Paulonis and Cox, 2003) reported the development of a control performance monitoring system spanning over 14,000 PID loops at the Eastman Chemical Company. Industrial case studies (Thornhill *et al.*, 1999; Miller *et al.*, 1998; Harris *et al.*, 1996*b*; Perrier and Roche, 1992; Wein-

[1] Corresponding Author: qin@che.utexas.edu.
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stein, 1992; Desborough and Miller, 2002) have been published on the subject and minimum variance based performance indices are a part of many commercially available control performance monitoring packages.

More recently, academic research interest has shifted to the assessment of MIMO control systems using the minimum variance benchmark (Harris *et al.*, 1996*a*; Huang *et al.*, 1997; Huang, 1997). Harris *et al.* (Harris *et al.*, 1996*a*) reformulated an LQ control solution (Harris and MacGregor, 1987) and show that the optimally controlled process follows a finite $(d-1)th$-order moving average process where d is the maximum delay present in the interactor. They proposed a statistical test of minimum variance based on a cross-correlation of the interactor filtered output vector and past outputs. The minimum variance calculation involves time series modeling of the closed loop system, spectral factorization of the inverse interactor and subsequent solution of a matrix Diophantine equation.

Huang *et al.* (Huang *et al.*, 1997) introduced the unitary interactor as a means of avoiding spectral factorization. The unitary interactor matrix was used to develop an explicit solution to the singular LQ regulation problem by Peng and Kinnaert (Peng and Kinnaert, 1992) and can be used to derive MVC with arbitrary output weighting (Huang, 1997). The need for a process transfer function restricts the practical usefulness of these algorithms. Harris recently (Harris, 2004) established the statistical confidence for the quadratic type of indices like the MVC benchmark.

The MVC benchmark has drawbacks in practice and alternative benchmarks are proposed. One of the limitations is the requirement of the interactor matrix which is essentially a good part of the entire process model. Seppala et al. (Seppala *et al.*, 2002) propose the use of time series analysis to model the control error dynamics and from it to analyze interactions in the multivariable system. No prior information about the process delay structure is required. McNabb and Qin (McNabb and Qin, 2003; McNabb and Qin, 2005) demonstrate that the variance based monitoring index is insufficient for assessing the multivariate covariance of the control performance. As an alternative a covariance based monitoring index is proposed to measure the variance-covariance inflation in terms of the 'volume' of the variability. Another drawback of the existing literature is that little has been done regarding diagnosis. In contrast, a great deal of research has taken place in the area of multivariate process monitoring (MacGregor and Kourti, 1995; Qin, 2003). We argue that in the MIMO setting the worst performance directions should be analyzed from data to yield meaningful diagnosis information. Therefore, multivariate statistics should be applied for the diagnosis of the worst performance directions, much like its use in multivariate process monitoring. Further, the need for the integration of control performance monitoring and process monitoring is pointed out as both problems co-exist in a plant with the same data as the ultimate information source for diagnosis.

In this paper we seek to provide a critical (rather than complete) overview of the MIMO control performance area and point to a new direction of covariance-based monitoring. For a more complete literature review the reader is referred to (Jelali, 2006). This paper is organized as follows. A critical overview of the MIMO control performance monitoring literature is given with some effort to unify some well-known methods. MIMO control performance indices based on the covariance is highlighted. Poor performance diagnosis is conducted by analyzing the worst performance directions using generalized eigenvalue analysis of two covariance matrices. We further propose to have the benchmark covariance as user-defined, rather than from a theoretical calculation. The user-defined benchmark can be a period of operation data that are taken from an exemplary operation. Since the benchmark is not necessarily a lower bound, the diagnosis results from the generalized eigenvector analysis include directions in which the performance deteriorates and those in which the performance improves. The worst performance directions are then analyzed with a proposed contribution analysis that leads to controlled variables or loops most responsible for the performance deterioration. The paper ends with a few concluding remarks.

2. OVERVIEW OF MIMO CONTROL PERFORMANCE MONITORING

2.1 *Minimum Variance Benchmark*

A MIMO process can be represented by the following equation:

$$y(k) = G(q)u(k) + H(q)e(k)$$

where $G(q)$ is the process transfer function matrix which contains possible time delays, $e(k)$ is the white noise innovation and $H(q)$ is the transfer function matrix of the disturbance. For SISO processes $G(q)$ can be represented by

$$G(q) = \tilde{G}(q)q^{-d} \tag{1}$$

where d is the time delay and $\tilde{G}(q)$ is time delay free. If we assume $G(q)$ has no zeros outside the unit circle, $\tilde{G}(q)$ is invertible. For simplicity we assume $G(q)$ has no zeros outside the unit circle except for the time delays.

For MIMO processes the time delays appear in a more complex form. The conventional approach is to find a unitary interactor matrix $D(q)$ such that (Peng and Kinnaert, 1992; Huang and Shah, 1997)

$$\tilde{G}(q) = D(q)G(q) \tag{2}$$

is full rank when $q^{-1} \to 0$, where $D^T(q^{-1})D(q) = I$, that is, $D(q)$ is a unitary matrix. Several methods are available to calculate the interactor matrix from the process model.

By examining the analogy between (1) and (2) we can express $G(q)$ as a product of two parts:

$$G(q) = D^{-1}(q)\tilde{G}(q) = D^T(q^{-1})\tilde{G}(q) \tag{3}$$

where $D^T(q^{-1})$ is analogous to the time delay in (1). Since $H(q)$ is a rational transfer function matrix of the disturbance without time delay, $D(q)H(q)$ should contain some positive factors of q. Denoting

$$D(q)H(q) = \sum_{i=1}^{d} F_i q^i + R(q) \tag{4}$$

where $R(q)$ contains no positive factors of q. We can now express the process output as

$$\begin{aligned} y(k) &= D^T(q^{-1})D(q)[G(q)u(k) + H(q)e(k)] \\ &= D^T(q^{-1})[\tilde{G}(q)u(k) + \sum_{i=1}^{d} F_i e(k+i) + R(q)e(k)] \end{aligned} \tag{5}$$

The innovation sequence $e(k)$ is known up to the current time k once $y(k)$ is measured, but $e(k+i)$ for $i = 1, \ldots, d$ are not known. Therefore, the feedback control $u(k)$ cannot do anything about the $e(k+i)$ terms. $u(k)$ can only be related to $e(k-i) \quad (i \geq 0)$ terms.

By defining the filtered output and using the results in (5),

$$\begin{aligned} \tilde{y}(k+d) &= D(q)y(k) \\ &= \sum_{i=1}^{d} F_i e(k+i) + \underbrace{R(q)e(k) + \tilde{G}(q)u(k)}_{\sum_{j=0}^{\infty} F_{-j} e(k-j)} \end{aligned} \tag{6}$$

For all possible feedback control the second and third terms of (6) can be expressed as past innovations. Further denoting

$$\tilde{y}_{mv}(k+d) = \sum_{i=1}^{d} F_i e(k+i)$$

and using the fact that $\tilde{y}(k)$ is stationary and $e(k)$ is white noise,

$$\begin{aligned} cov\{\tilde{y}(k)\} &= cov\{\tilde{y}_{mv}(k+d)\} + cov\{e(k-j)\ terms\} \\ &\geq cov\{\tilde{y}_{mv}(k)\} \end{aligned} \tag{7}$$

and the MIMO minimum variance control is achieved by

$$u(k) = -\tilde{G}^{+}(q)R(q)e(k) \tag{8}$$

where $\tilde{G}(q)$ is full rank as $q^{-1} \to 0$. Note that pseudo-inverse is used here since $\tilde{G}(q)$ can be non-square.

The above derivation gives the MIMO MVC control law which actually achieves *minimum covariance* in the filtered output. This result, however, has not been widely recognized so far. We make a few remarks about this derivation.

Remark 1. The above MIMO MVC derivation is straightforward and analogous to the SISO MVC derivations (Åström, 1970). The MIMO MVC control law is explicitly expressed in terms of the innovations which correspond to the process output data.

Remark 2. The MIMO MVC law actually achieves minimum covariance in the filtered output, as depicted in (7), which make the difference of the two covariances positive semi-definite. As a consequence, MIMO MVC achieves minimum variance in all possible directions in the filtered output space.

Remark 3. All MVC based performance monitoring methods require the knowledge of $D(q)$ implicitly or explicitly, which is calculated by various means. Huang and Shah (Huang and Shah, 1997) start from the transfer function form, while McNabb and Qin (McNabb and Qin, 2003) start with the state space form. Both methods require only the first d Markov parameter matrices of the process, instead of the entire process model. However, these Markov parameters are difficult to obtain unless some form of identification tests are performed.

Remark 4. Often the sum of the output variances is chosen as a benchmark, which is

$$\begin{aligned} tr[cov(y_{mv}(k))] &= Ey_{mv}^T(k)y_{mv}(k) \\ &= E\left(\tilde{y}^T(k+d)D(q)D^T(q^{-1})\tilde{y}(k+d)\right) \\ &= E\left(\tilde{y}^T(k+d)\tilde{y}(k+d)\right) \\ &= tr[cov(\tilde{y}_{mv}(k))] \\ &= tr\left\{\sum_{i=1}^{d} F_i R_e F_i^T\right\} \end{aligned} \tag{9}$$

where $R_e = cov(e(k))$. We will argue later that the sum of variances is an incomplete measure of the overall output covariance.

The minimum variance parameters F_i can be estimated from routine operational data. The FCOR algorithm (Huang *et al.*, 1997) pre-estimates the innovations $e(k)$ and then performs correlation analysis to estimate F_i. The subspace projection method of McNabb and Qin (2003) represents the past innovations $e(k-j)$ in terms of past data $y(k-j)$ $(for\ j \geq 0)$ and uses the projection error as $\sum_{i=1}^{d} F_i e(k+i)$. These two algorithms are essentially equivalent.

Harris (Harris, 2004) discusses the issue of the variance of the minimum variance estimated from data, which is an important issue that has not been discussed before. Although many algorithms that calculate the minimum variance are numerically equivalent, the algorithms that estimate the coefficients F_i from closed loop data can differ in terms of statistical efficiency or in the variance of the estimates. The FCOR algorithm, for example, first estimates the innovations sequence and then estimates the coefficients F_i. This procedure resembles the two stage least squares algorithm in (Kashyap and Nashburg, 1974), which is shown to be simple but not efficient in (Mayne and Firoozan, 1982), where an improved efficient algorithm is also proposed.

2.2 *Alternative Performance Benchmarks*

The limitations of the MVC based benchmark are

(1) The benchmark is based solely on time delay restrictions; other restrictions such as hard constraints are not considered.
(2) The minimum variance, although achievable under ideal situations, leads to a non-robust controller. This is characterized by excessive input moves that are usually inherent to MVC.
(3) Only disturbance rejection performance is considered.
(4) The requirement of the interactor is restrictive in practice.

To overcome these limitations, many alternative benchmarks have been studied. Huang and Shah (1998) allow the user to specify the noise decay rate after the interactor order, which has built-in robustness in the benchmark. This approach, however, still requires the interactor matrix. In a similar effect but for the SISO case, Horch and Isaksson (1999) introduced a finite closed-loop pole in the benchmark controller to enhance robustness.

A departure from the use of the interactor matrix is given in the work of Huang et al. (Huang *et al.*, 2005) where, instead of using the exact interactor matrix, only the order of the interactor is used. This method removes the need to estimate the interactor matrix. The time series analysis approach of Seppala et al. (Seppala *et al.*, 2002) does not require any information about the interactor matrix. The control error is analyzed as a time series to detect whether the control loops are interacting or not. Recent work of Harris and Yu (Harris and Yu, 2003) performs degree of freedom analysis to monitor the status of constraints and long run behavior of the control performance.

To address the issue of excessive input moves of MVC, Kadali and Huang (Kadali and Huang, 2002) propose to use LQG as a benchmark. A drawback of this benchmark is the requirement of the entire process model.

As the ultimate multivariable controller in industry is model predictive control (MPC), several attempts have been made to assess the performance of MPC. Loquasto and Seborg (Loquasto and Seborg, 2003) propose the use of similarity factors and pattern recognition to determine the MPC performance is normal or abnormal, and if there is a significant disturbance change. Schaffer and Cinar (Schaffer and Cinar, 2004) propose a knowledge based approach for MPC performance monitoring. Given the complexity of MPC that involves model errors, disturbance changes, optimal target settings, active constraint sets, and controller tuning, the MPC performance monitoring is largely an unsolved problem.

3. COVARIANCE-BASED PERFORMANCE INDEX AND DIAGNOSIS

In MIMO control performance monitoring, the process output variance is an important parameter and the associated performance index may be defined as the ratio of minimum variance to actual variance

$$\eta = \frac{tr\,\{cov(\tilde{y}_{mv}(k))\}}{tr\,\{cov(\tilde{y}(k))\}} \tag{10}$$

The value of variance index η is between 0 and 1, where the upper bound 1 corresponds to the minimum variance. In the above equation, however, only the diagonal elements of covariance matrix are taken into comparison and the information from the off-diagonal elements is completely ignored (McNabb and Qin, 2003).

To account for the variability that is accurately represented by the covariance matrix, a volume-like performance index is more appropriate, which is defined by the ratio of the determinants as follows,

$$I_v = \frac{\det\{cov(\tilde{y}_{mv}(k))\}}{\det\{cov(\tilde{y}(k))\}} \tag{11}$$

Since the determinant is the product of all eigenvalues of the covariance matrix, this index defines exactly the volume ratio.

Denoting the eigenvalues of $cov(\tilde{y}_{mv}(k))$ and $cov(\tilde{y}(k))$ as λ_i^{mv} and λ_i, respectively, the variance based and covariance based performance indices can be rewritten as

$$\eta = \frac{\sum \lambda_i^{mv}}{\sum \lambda_i} \quad (12)$$

$$I_v = \frac{\prod \lambda_i^{mv}}{\prod \lambda_i} \quad (13)$$

Although both indices use information from the eigenvalues, the volume-like index takes into account the covariance information and interactions among variables.

To find a direction in $\tilde{y}(k)$ along which the worst suboptimality occurs, we find the direction p with $\|p\| = 1$ and project $\tilde{y}(k)$ and $\tilde{y}_{mv}(k)$ to this direction:

$$\begin{aligned} \Pi_p \tilde{y}(k) &= p^T \tilde{y}(k)/p^T p &= p^T \tilde{y}(k) \\ \Pi_p \tilde{y}_{mv}(k) &= p^T \tilde{y}_{mv}(k)/p^T p &= p^T \tilde{y}_{mv}(k) \end{aligned}$$

The variance of the projections are, respectively,

$$\begin{aligned} var(\Pi_p \tilde{y}(k) &= p^T cov(\tilde{y}(k))p \\ var(\Pi_p \tilde{y}_{mv}(k) &= p^T cov(\tilde{y}_{mv}(k))p \end{aligned}$$

The direction p along which the largest variance ratio occurs is

$$p = arg\ max \frac{p^T cov(\tilde{y}(k))p}{p^T cov(\tilde{y}_{mv}(k))p} \quad (14)$$

The direction of p after maximization give the direction with the most potential to improve the performance. The solution to this problem is a generalized eigenvector problem,

$$cov(\tilde{y}(k))p_i = \mu_i cov(\tilde{y}_{mv}(k))p_i$$

where p_i is the generalized eigenvector corresponding to the i^{th} largest generalized eigenvalue μ_i. The volume of the suboptimality or variance inflation due to poor control performance is:

$$\prod_{i=1}^{l} \mu_i$$

where l is the number of selected directions. The volume-based performance can be defined as

$$I_v(l) = \prod_{i=1}^{l} {\mu_i}^{-1}$$

It is straight forward to show from (7) that for all possible projections Π,

$$cov\left(\Pi \tilde{y}_{mv}(k)\right) \le cov\left(\Pi \tilde{y}(k)\right)$$

Therefore, $\mu_i \ge 1$ and I_v is between zero and one. When $\tilde{y}(k)$ achieves the minimum variance performance, I_v approaches one. On the other hand, I_v close to zero indicates poor performance.

4. USER-DEFINED BENCHMARK

The calculation of minimum variance output y_{mv} , however, requires a priori knowledge of the plant and even the model of the system, which is not attractive to implement in practice. Therefore, a user-defined reference is chosen as the benchmark, and the generalized eigenvalue analysis is implemented. The user-defined reference can be a period of "golden" operation data from the process during which desirable control performance was achieved. It could be a period of operation data right after a new controller has been commissioned successfully. It could also used for rolling period monitoring, for instance, benchmarking the performance of the current week against that of last week. Denoting the benchmark data as period I and the monitored data as period II, the direction along which the variance inflation occurs the most is given by

$$p = \arg\ \max \frac{p^T cov(y_{II})p}{p^T cov(y_I)p} \quad (15)$$

The solution is the generalized eigenvector solution,

$$cov(y_{II})p = \mu cov(y_I)p \quad (16)$$

where μ is the generalized eigenvalue and p is the corresponding eigenvector. The direction p is referred to as the worst performance direction (WPD). In addition to the first generalized eigenvector, other subsequent eigenvectors with large enough eigenvalues (especially those much larger than 1) are also of remarkable suboptimality in control performance and should be examined to further improve the control performance.

Since the reference benchmark is not necessarily a minimum variance benchmark, there can be directions along which the monitored period II outperforms the benchmark period I. These directions correspond to the generalized eigenvalues that are significantly less than one, and the corresponding eigenvectors represent the directions with the smallest variance ratio of the monitored period over the benchmark period. These eigendirections constitute the subspace of improved performance over the benchmark. Trying to maintain the loop operations within this subspace will obviously benefit the process control performance.

It is also meaningful to assess the overall variability of the monitored period against the benchmark period by defining a volume-like performance index as follows,

$$I_v = \frac{\det\left\{cov(y_{II}(k))\right\}}{\det\left\{cov(y_I(k))\right\}} \quad (17)$$

This ratio, while greater than zero, can be greater than or less than one. If it is greater than one, the performance of the monitored is in general worse than the benchmark period and the worst performance directions of the monitored period should be examined. If, on the other hand, this index is significantly less than one, the directions corresponding to the smallest eigenvalues should be examined to understand where the performance has improved. Denoting μ_i, for $i = 1, 2, \ldots, n_y$ as the generalized eigenvalues in descending order, the volume based index in (17) can be rewritten as

$$I_v = \prod_{i=1}^{n_y} \mu_i^{-1} \quad (18)$$

which is easy to calculate once the generalized eigenvalues are calculated.

5. CASE STUDY

Industrial operating data collected from the DCS system of a wood waste burning power boiler are used here as the example to examine and verify the applicability of the user-defined performance assessment approach. The data set is composed of sample points with the sampling time of five seconds and three subsets of process variables (PV), the corresponding set-point (SP) and controller outputs (OP), respectively. The data processing is applied to the controller error terms, i.e., PV-SP. All these data points are preprocessed by scaling to zero mean and unit variance in every loop. The detailed physical description for these loops is given in Table 1.

The covariance based monitoring is performed on a data set with 150,000 consecutive data points. Here the benchmark period I consists of the first 66,000 samples, while the period II containing 84,000 points is monitored with respect to the benchmark period. It is suspected that the period II has experiences some changes in the performance. The computation results from the proposed monitoring procedure are depicted in Fig.1. The upper-left subplot shows the maximal and minimal eigenvalues, while the lower-right one shows the full spectrum of eigenvalues and their cumulative percentage. It can be easily seen from the plot that the largest eigenvalue is far above one, which implies that the control performance of period II in this eigenvector direction is much worse than that of the benchmark. The loading score plots for the largest and smallest eigenvector directions are given in Fig.1(b) and (c), respectively. It is clear that the variable 4, i.e. loop FC0902, contributes most significantly in the first eigendirection. Thus we may conclude that the control performance of monitored period along the largest eigendirection, especially loop FC0902, deteriorated significantly. In other words, there exists a great margin to improve the performance by re-tuning along this direction as well as the loop FC0902. This can serve as an instructive tool for control engineers to maintain the control system. On the other hand, the smallest eigenvector stands for the direction of improved performance over the benchmark. Fig 1(c) shows that loops 5 and 3 have large contributions to the improved performance.

6. CONCLUDING REMARKS

MIMO control performance monitoring has enjoyed great development recently as it is one of the most important issues in practice after the control design. The minimum variance benchmark is usually considered a good starting point although it requires significant process information. For MIMO performance monitoring we demonstrate in this paper that covariance based monitoring is more appropriate when strong interactions occur among controlled variables. The covariance-based monitoring is extended to benchmarking any two covariance matrices and diagnosis of worse or better performance directions is developed.

Due to limited space several related issues could not be covered in this paper but they are important. One is the deterministic performance loss due to loop oscillations and the need for setpoint tracking. Another is the dual task of control performance monitoring and statistical process monitoring. The current situation is that both issues are studied assuming the other part is problem free. In practice the problems co-exist and only routine operation data are available to tell one problem from another. The integration of control performance monitoring and process monitoring deserves further study.

7. REFERENCES

Åström, K. J. (1976). State of the art and needs in process identification. In: *Proc. of Conf. Process Control-II, AIChE Symposium Series.* pp. 184–194.

Åström, Karl J. (1970). *Introduction to Stochastic Control Theory.* Academic Press. San Diego, California.

Desborough, Lane and Randy Miller (2002). Increasing customer value of industrial control performance monitoring – honeywell's experience. In: *Chemical Process Control - CPC VI.* CACHE. Tuscon, Arizona. pp. 169–189.

Harris, T., F. Boudreau and J.F. Macgregor (1996*a*). Performance assessment of multivariable feedback controllers. *Automatica* **32**(11), 1505–1518.

Harris, T. J. (1989). Assessment of control loop performance. *Can. J. Chem. Eng.* **67**(10), 856–861.

Harris, T. J. and C. T. Seppala (2002). Recent developments in controller performance monitoring and assessment techniques. In: *Chemical Process Control - CPC VI.* CACHE. Tuscon, Arizona. pp. 208–222.

Harris, T.J. (2004). Statistical properties of quadratic-type performance indices. *J. Proc. Cont.* **14**, 899–914.

Harris, T.J. and J.F. MacGregor (1987). Design of multivariable linear-quadratic controllers using transfer functions. *AIChE J.* **33**(9), 1481–1495.

Harris, T.J. and W. Yu (2003). Analysis of multivariable controllers using degree of freedom data. *Int. J. Adaptive Control and Signal Processing* **17**, 569–588.

Harris, T.J., C.T. Seppala and L.D. Desborough (1999). A review of performance monitoring and assessment techniques for univariate and multivariate control systems. *J. Proc. Cont.* **9**, 1–17.

Harris, T.J., C.T. Seppala, P.J. Jofriet and B.W. Surgenor (1996*b*). Plant-wide feedback control performance assessment using an expert system framework. *Control Engineering Practice* **4**(9), 1297–1303.

Hoo, K. A., M. J. Piovoso, P. D. Schnelle and D. A. Rowan (2003). Process and controller performance monitoring: overview with industrial applications. *Int. J. Adaptive Control and Signal Processing* **17**, 635–662.

Horch, A. and R. Isaksson (1999). A modified index for control performance assessment. *J. Proc. Cont.* **9**, 475–483.

Huang, B. (1997). Multivariate Statistical Methods For Control Loop Performance Assessment. PhD thesis. University of Alberta.

Huang, B. and S.L. Shah (1997). Feedback control performance assessment of non-minimum phase MIMO systems. In: *AIChE Annual Meeting*. Los Angeles.

Huang, B. and S.L. Shah (1998). Practical issues in multivariable feedback control performance assessment. *J. Proc. Cont.* **8**, 421–430.

Huang, B. and S.L. Shah (1999). *Performance Assessment of Control Loops: Theory and Applications*. Advances in Industrial Control. Springer-Verlag. London, Great Britain.

Huang, B., S.L. Shah and K.Y. Kwok (1997). Good, bad or optimal? performance assessment of MIMO processes. *Automatica* **33**(6), 1175–1183.

Huang, B., S.X. Ding and N. Thornhill (2005). Practical solutions to multivariate feedback control performance assessment problem: reduced a priori knowledge of interactor matrices. *J. Proc. Cont.* **15**, 573–583.

Jelali, M. (2006). An overview of control performance assessment technology and industrial applications. *Control Eng. Practice* **14**, 441 – C466.

Kadali, R. and B. Huang (2002). Controller performance analysis with lqg benchmark obtained under closed loop conditions. *ISA Transactions* **41**, 521–537.

Kashyap, R.L. and R.E. Nashburg (1974). Parameter estimation in multivariate stochastic difference equations. *IEEE Trans. Auto. Cont.,* **19**, 784.

Kozub, D.J. (1996). Controller performance monitoring and diagnosis: experiences and challenges. In: *Fifth Int. Conf. on Chemical Process Control* (J.C. Kantor, C.E. Garcia and B.C. Carnahan, Eds.). AIChE and CACHE. Tahoe, CA. pp. 83–96.

Loquasto, F. and D. Seborg (2003). Model predictive controller monitoring based on pattern classification and pca. In: *Proc. of ACC*. Vol. 3. pp. 1968 – 1973.

MacGregor, J.F. and T. Kourti (1995). Statistical process control of multivariate processes. *Control Engineering Practice* **3**(3), 403–414.

Mayne, D.Q. and F. Firoozan (1982). Linear identification of arma processes. *Automatica,* **18**, 461–466.

McNabb, C. A. and S. J. Qin (2003). Projection based MIMO control performance monitoring – I. Covariance monitoring in state space. *J. Proc. Cont.* 739-759.

McNabb, C. A. and S. Joe Qin (2005). Projection based MIMO control performance monitoring – II. Measured disturbances. *J. Proc. Cont.* **15**, 89–102.

Miller, R., L. Desborough and C. Timmons (1998). Citgo's experience with controller performance assessment. In: *NPRA 1998 Computer Conference*. San Antonio, Texas.

Paulonis, M.A. and J.W. Cox (2003). A practical approach for large-scale controller performance assessment, diagnosis, and improvement. *J. Proc. Cont.* **13**, 155–168.

Peng, Youbin and Michel Kinnaert (1992). Explicit solution to the singular LQ regulation problem. *IEEE Trans. Auto. Cont.* **37**(5), 633–636.

Perrier, M. and A. Roche (1992). Towards millwide evaluation of control loop performance. In: *Control Systems '92*. Whistler, British Columbia.

Qin, S. J. (2003). Statistical process monitoring: Basics and beyond. *J. Chemomotrics* **17**, 480–502.

Qin, S.J. (1998). Control performance monitoring – a review and assessment. *Comput. Chem. Eng.* **23**, 178–186.

Schaffer, J. and A. Cinar (2004). Multivariable mpc system performance assessment, monitoring, and diagnosis. *J. Proc. Cont.* **14**, 113–129.

Seem, J. E. (1998). A new pattern recognition adaptive controller with application to hvac systems. *Automatica,* **34**, 969–982.

Seem, J. E. (2006). An improved pattern recognition adaptive controller. In: *Proceedings of*

the 2006 American Control Conference. Minneapolis, MN.
Seppala, C.T., T.J. Harris and D.W. Bacon (2002). Time series methods for dynamic analysis of multiple controlled variables. *J. Proc. Cont.* **12**, 257–276.
Thornhill, N.F., M. Oettinger and P. Fedenczuk (1999). Refinery-wide control loop performance assessment. *J. Proc. Cont.* **9**, 109–124.
Weinstein, B. (1992). A sequential approach to the evaluation and optimization of control system performance. In: *1992 ACC*. Chicago. pp. 2354–2358.

Table 1. The name tag and description of ten loops from a power boiler unit

Variable No.	Loop Identification	Description
1	FC0400	PB feed water flow control
2	FC0618	Oil burner air flow control
3	FC0620	Bark-air flow control
4	FC0902	Bark feed rate control
5	FC0922	Bark air firing control
6	LC0403	PB drum level control
7	PC0603	Combustion air pressure
8	PC0609	Furnace pressure control
9	PC0622	Over-fire air pressure
10	PC0904	Steam head pressure control

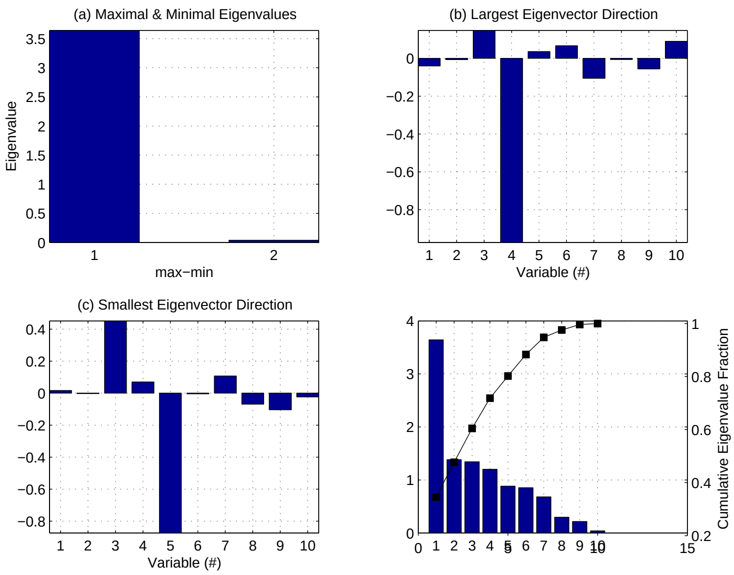

Fig. 1. Generalized eigen-analysis results for the period II against the user-defined benchmark period I with (a) the maximal and minimal eigenvalues; (b) the eigenvector direction corresponding to the maximum eigenvalue; (c) the eigenvector direction corresponding to the minimum eigenvalue; (d) the eigenvalue spectrum and the corresponding cumulative fractions.