A Study of Performance Monitoring and Diagnosis Method for Multivariable MPC Systems

Seung Yong Lee*, Seung Hun Youm** , and Kwang Soon Lee***

* Department of Chemical Engineering, Sogang University, Seoul, South Korea
(Tel : +82-2-705-8477; E-mail: puljongdar@sogang.ac.kr)
**Department of Chemical Engineering, Sogang University, Seoul, South Korea
(Tel : +82-2-705-8477; E-mail: huni@sogang.ac.kr)
***Department of Chemical Engineering, Sogang University, Seoul, South Korea
(Tel : +82-2-705-8477; E-mail: kslee@ccs.sogang.ac.kr)

Abstract: Method for performance monitoring and diagnosis of a MIMO control system has been studied aiming at application to model predictive control (MPC) for industrial processes. The performance monitoring part is designed on the basis of the traditional SPC/SQC method. To meet the underlying premise of Schwart chart observation that the observed variable should be univariate and independent, the process variables are decorrelated temporally as well as spatially before monitoring. The diagnosis part was designed to identify the root of performance degradation among the controller, process, and disturbance. For this, a method to estimate the model-error and disturbance signal has been devised. The proposed methods were evaluated through numerical examples.

Keywords: Control performance, MIMO case monitoring, Model predictive control, Diagnosis

1. INTRODUCTION

Model predictive control (MPC) has now more than twenty years of the history in industrial application. According to a survey paper [1], there have been more than 4,500 process implementation have been reported. Industries, processes are necessarily subject to aging, modifications, and changes in operating conditions. All theses result in performance deterioration of MPC which is optimized for the original process situation. Since unlike the PID controller MPC is not easy to maintain by operation personnel, a strong need for on-line performance monitoring and diagnosis has been raised from industries.

For SISO controllers typified by PID, the ratio of the control error variance between the present controller and the minimum variance controller, which was suggested by Harris [2], has been accepted as a standard control performance index. Qin [3] extended this idea to the case when the process model includes the disturbance model. Stanfelj et al. [4] proposed that the cross correlation test can be used to distinguish between the plant model error and disturbance model error. All these and other contributions have enabled reliable assessment of SISO controllers and commercial web-based services control loop assessment.

Unlike the SISO case, in MIMO control performance assessment, there have not been yet generally accepted methods. Huang et al. [5] and Harris et al. [6] extended the MVC-based SISO assessment method to the MIMO case. However, the requirement to identify the time-delay distribution between inputs and outputs hampers the usability of the method. Kesavan and Lee [7] proposed several diagnosis tools that are based on the prediction error (PE) and demonstrated their efficacy through numerical examples. Since the PE can be calculated when the disturbance model is available while present commercial MPC's use only the input-output part of the model, the Kesavan's method will not be easy to apply to the present commercial MPC's.

Considering the above general background, the purpose of this research has been placed in developing more comprehensive and practical performance monitoring and diagnosis methods for industrial MPC's. The performance monitoring method was devised based on the traditional univariate SPC/SQC technique [8]. For this, a whitening filter and PCA were introduced to decorrelate the process variables that are temporally as well as spatially correlated. For diagnosis, a method to identify the model-plant mismatch has been proposed. Using this method, the cause of control performance deterioration can be found among the controller, process, and disturbance, but not into further details. The proposed methods have been evaluated with numerical systems.

2. PERFORMANCE MONITORING

The traditional Schwart (and CUSUM) chart monitoring gives valid interpretation only when the observed variable is uncorrelated with other monitored variables and doesn't have temporal correlation. On the other hand, process variables are usually inter-correlated and subject to dynamics. This hampers the use of well-developed SPC/SQC techniques in the process industries. In this research, we devised a decorrelation procedure so that the well-developed SPC/SQC method can be used as a monitoring tool for process variables under MIMO control.

2.1 Temporal Decorrelator – Whitening Filter

Using control error $\{e^{m}(t)\}$ measured under in-control state, a multivariable ARMA model is identified in the state space form using the N4SID technique [9].

$$x(t+1) = Ax(t) + Kv(t) \tag{1}$$

$$e^m(t) = Cx(t) + v(t) \quad (2)$$

where $v(t)$ is zero-mean white noise sequence. The temporal decorrelator (whitening filter) can be directly obtained from this model through simple rearrangement.

$$x(t+1) = (A-KC)x(t) + Ke^m(t) \quad (3)$$

$$v(t) = e^m(t) - Cx(t) \quad (4)$$

2.2 Spatial Decorrelator

To the collection of whitened signal $\{v(t)\}$ for the in-control state measurements, the principal component analysis (PCA) is applied such that

$$V \approx PS \quad (5)$$

where $V = [v(1) \cdots v(m)]$; S, P represent score and loading matrices for the major principal components, respectively. When a new $v(t)$ is obtained during on-line monitoring, it is projected on P to get the score such that

$$s(t) = P^T v(t) \quad (6)$$

Through this procedure, the spatial correlation between the elements of $v(t)$ is resolved. The elements $s_i(t)$'s are temporally as well as spatially uncorrelated.

2.3 Schwart Chart Monitoring

Monitoring of $s_i(t)$'s follows the standard Schwart and CUSUM chart procedure. For example, in the Schwart chart, x-bar which is defined for a disjoint subgroup for n-consecutive $t_i(t)$'s as

$$\bar{\bar{x}} = \frac{s_i(t) + \cdots + s_i(t+n-1)}{n} \quad (7)$$

is monitored for each . The two control limits, UCL and LCL, are determined as

$$UCL = \bar{\bar{X}} + \alpha \bar{R} \quad (8)$$

$$LCL = \bar{\bar{X}} - \alpha \bar{R} \quad (9)$$

where $\bar{\bar{x}}$ and $\bar{R}$ are defined for the in-control state data such that

$$\bar{\bar{x}} = \frac{\bar{x}_1 + \bar{x}_2 + \cdots \bar{x}_n}{n} \quad \text{for a sufficiently large N} \quad (10)$$

$$\bar{\bar{R}} = \frac{R_1 + R_2 + \cdots R_n}{n} \quad \text{for a sufficiently large N} \quad (11)$$

where $R = \bar{x}_{highest} - \bar{x}_{lowest}$ within each group.

and α is given in relation to the specified risk level and can be found in a standard text book like [10].

3. DIAGNOSIS

The cause of poor control performance can be classified into three: inadequate controller tuning, large plant-model mismatch, and large disturbance. There are different ways to identify the cause. However, the method based on closed-loop identification is thought to give the most lucid conclusion. In this research, we propose a method to estimate the model error and the disturbance signal at the same time. From this result, one can determine which of the three would be most important cause of the performance degradation.

3.1 Identification of plant-model mismatch

Figure 1 shows a block-diagram that represents the situation of the proposed identification experiment. For unbiased model estimate, a zero-mean dither signal $\hat{u}(t)$ is superimposed at the input port.

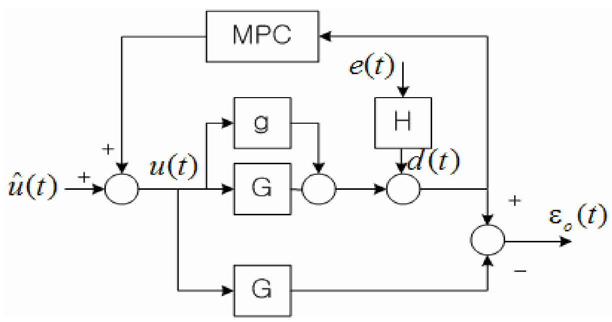

Fig. 1. Block diagram representation of the model error identification experiment.

The block diagram analysis shows that the output error is given by

$$\varepsilon_o(t) = g(q)(u(t) + \hat{u}(t)) + d(t) \quad (12)$$

In the above, $\hat{u}(t)$ is uncorrelated with $d(t)$, which implies $R_{d\hat{u}}(\tau) = 0$ for all τ . Hence, we have the relation

$$R_{\varepsilon_o \hat{u}}(\tau) = g(q)(R_{u\hat{u}}(\tau) + R_{\hat{u}}(\tau) \quad (13)$$

and can estimate $g(q)$ through the least squares method. Once the estimate of $\hat{g}(q)$ is obtained, the disturbance signal can be reproduced according to

$$\hat{d}(t) = \varepsilon_o(t) - \hat{g}(q)(u(t) + \hat{u}(t)) \tag{14}$$

In this research, $g(q)$ is represented by a MIMO FIR model and the impulse response coefficient matrices are determined using the least squares (LS) method. To avoid the co-linearity problem, the partial least squares (PLS) method is employed instead LS method.

The model error estimate $\hat{g}(q)$ can be graphically represented in the frequency domain as an array of $[g_{ij}(e^{j\omega})/G_{ij}(e^{j\omega})]$, $\omega \in [0, \pi]$ and we can locate what part of the model raise the problem. $\hat{g}(q)$ can also be used to update the process model $G(q)$ on which present MPC is based.

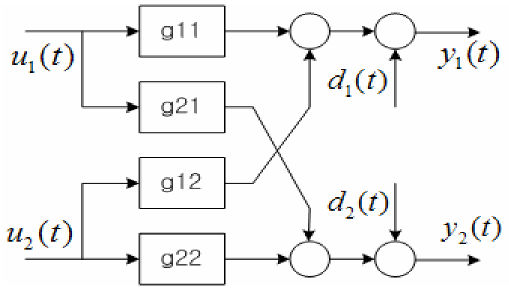

Fig. 2. A 2×2 system with output disturbance.

One thing that has to be remembered is that the disturbance estimation is possible only when the whole $g(q)$, not a part of $g(q)$, is estimated. This can be illustrated using Fig. 2. If only $g_{11}(q)$ is estimated using $\{u_1(t), y_1(t)\}$, the disturbance estimate according to (12) represents

$$y_1(t) - \hat{g}_{11}(q)u_1(t) = d_1(t) + g_{12}(q)u_2(t) \neq d_1(t) \tag{15}$$

If both the model error and disturbance estimates are small, one may suspect the controller as the cause of the poor performance.

3.2 Cross-correlation Test

The previous model error identification method concerns only the input-output part of the process model. Since the most commercial MPC's are designed based on $G(q)$, the method can be applied to the existing MPC systems although the perturbation tests of a controlled process need a concession from operators.

Unlike the previous method, the cross-correlation test can be conducted without closed loop perturbation but only when both $G(q)$ and $H(q)$ are available. In this respect, it is inadequate to implement in the present commercial MPC's. Nevertheless, this method is considered as a possible future supplement to the model error identification method.

The test is conducted between the input $u(t)$ and the prediction error $\varepsilon(t)$ and the experimental situation is shown Fig. 3.

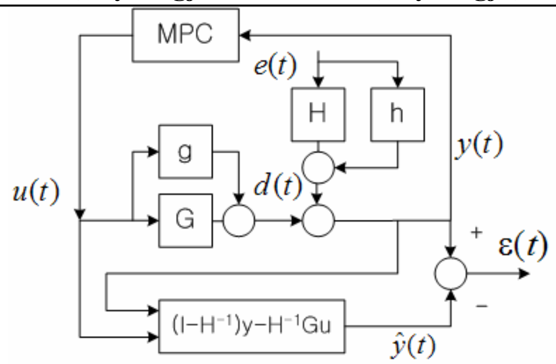

Fig. 3. The situation diagram for the cross-correlation test

The prediction error is represented as [11]

$$\varepsilon(t) = y(t) - \hat{y}(t) = H(q)^{-1}(y(t) - G(q)u(t)) \tag{16}$$

From the fact that $y(t) = (G(q) + g(q))u(t) + (H(q) + h(q))e(t)$, the model error effect on the prediction error can be shown as

$$\varepsilon(t) = (I + H(q)^{-1}h(q))e(t) + H(q)^{-1}g(q)u(t) \tag{17}$$

Under closed-loop control, u(t) is necessarily affected by $e(t-\tau)$. Thus $\varepsilon(t)$ and $u(t-\tau)$, $\tau \geq 0$ are independent only when $g(q) = h(q) = 0$. Also, under the hypothesis that $\varepsilon(t)$ and $u(t-\tau)$, $\tau \geq 0$ are independent, it holds [12] that

$$\hat{R}_{\varepsilon u}^N(\tau) = \frac{1}{N}\sum_{t=1}^{N}\varepsilon(t)\hat{u}(t-\tau)^T \tag{18}$$

satisfies

$$\sqrt{N}\hat{R}_{\varepsilon u}^N(\tau) \to N(0, P_1), \quad P_1 = \sum_{k=-\infty}^{\infty} R_\varepsilon(k)R_u(k) \tag{19}$$

Using this property, we can test if $\varepsilon(t)$ and $u(t-\tau)$ are independent, or equivalently, the model errors for both $G(q)$ and $H(q)$ are negligible.

3.2 Prediction Error Monitoring under MPC Detuning [7]

It is obvious that $\varepsilon(t)$ is unaffected by any change in the controller tuning as far as $g(q) = h(q) = 0$. The detuning technique is considered as another supplement technique to the model error identification method. But it shares the same drawback as that of the cross-correlation test.

4. NUMERICAL EXAMPLE

In this example, we demonstrate the performance of the model-error identification method for a 2×2 system.
The true process is represented by

$$y(t) = Gu(t) + W\begin{bmatrix} e_1(t) \\ e_2(t) \end{bmatrix} \tag{20}$$

where $e_i(t),\ i=1,2$ are white noise processes with $N(0,1)$. $G(q)$ is assumed to be

$$G(q)=\begin{bmatrix}\dfrac{0.020q+0.018}{q^2+1.684q+0.660} & \dfrac{0.0044q+0.0041}{q^2-1.803q+0.8119}\\ \dfrac{0.016q+0.014}{q^2-1.625q+0.659} & \dfrac{0.0086q+0.0081}{q^2-1.844q+0.85}\end{bmatrix}. \quad (21)$$

the real process is

$$G_{process}(q)=\begin{bmatrix}\dfrac{0.223q+0.020}{q^2+1.684q+0.660} & \dfrac{0.0049q+0.0045}{q^2-1.803q+0.8119}\\ \dfrac{0.018q+0.016}{q^2-1.625q+0.659} & \dfrac{0.0089q+0.0084}{q^2-1.844q+0.85}\end{bmatrix} \quad (22)$$

W is an integrator.

$$W=\begin{bmatrix}\dfrac{1}{1-z} & 0\\ 0 & \dfrac{0.5}{1-z}\end{bmatrix} \quad (23)$$

For model error identification, independent PRBS's (with increasing the clock period for signal spectrum adjustment) were applied to $\hat{u}_1(t)$ and $\hat{u}_2(t)$, respectively.

In Fig.4, the estimated impulse response coefficients of the model-plant mismatch are shown in comparison of the true values. We can see that the proposed method yields highly reliable results.

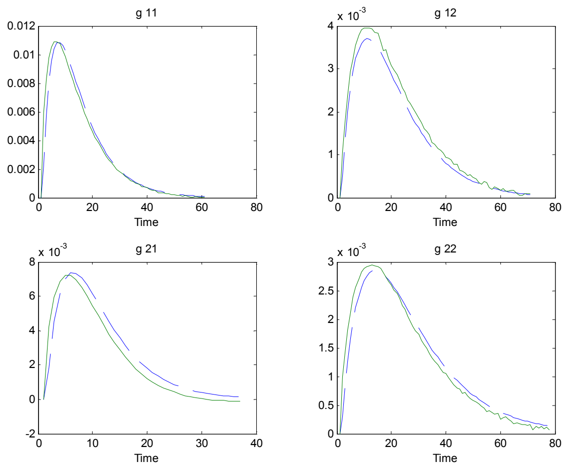

Fig. 4. Impulse response coefficients of the model-plant mismatch (solid line-estimated values, broken line- true values)

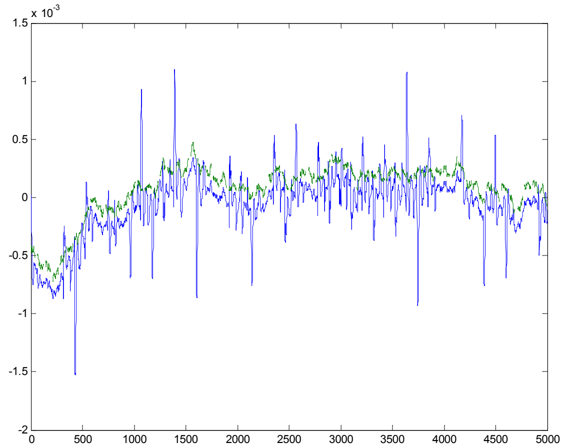

Fig. 5. Disturbance signals (solid line-estimated value, broken line-true value)

Fig.5 shows a part of the disturbance signals regenerated according to (14), which is compared with the true signals. this time, too, a satisfactory result was obtained.

5. CONCLUSION

In this paper, we presented several tools for monitoring and diagnosing the performance of multivariable control systems. The monitoring part is based on the well-established traditional SPC/SQC technique whereas the diagnosis part utilizes the closed-loop identification as the key technique. Through a number of different numerical tests, the proposed techniques are found to be effective and simple to apply. It is believed that the concepts presented in this paper can play as important alternatives to the currently exploited performance monitoring and diagnosis methods for MIMO control systems.

ACKNOWLEDGMENTS

This work was supported by the IMT 2000 (project number: 00015993) in 2003 by MOICE

REFERENCES

[1] G. Box, A. Luceno, *Statistical control by monitoring and feedback*, John Wiley, NY, 1997.

[2] T. J. Harris, "Assessment of control loop performance", *Can. J. chem. Engng.*, Vol. 67, pp 856-861, 1989.

[3] S. J. Qin, "Control performance monitoring-a review and assessment", *Computers and Chemical Engineering*, Vol. 23, pp 173-186, 1997.

[4] N. Stanfelj, T. E. Marlin and J. F. MacGregor, "Monitoring and diagnosing process control performance: the single-loop case", *Ind. Eng. Chem. Res.,* Vol. 32, pp 301-304, 1993.

[5] B. Huang, S. L. Shah, and E. L. Kwok, "On-line control performance monitoring of MIMO processes", *Proc. ACC*, pp. 1250-1254, 1995.

[6] T. J. Harris., F. Boudreau and J. F. MacGergor, "Performance assessment of multivariable feedbacn controllers", *AIChe Annual Meeting, Miami Beach*, Paper 182e, 1995.

[7] P. Kesavan and J. H. Lee, "Diagnostic tools for multivariable model-based control systems", Ind. Eng.

Chem, Vol. 36, pp. 2725-2738, 1997.
[8] C. L. Mamzic, *Statistical process control*, ISA, 1995.
[9] P. Von Overschee and B. BeMoore, "N4SID: subspace algorithms for the identification of combined Deterministic-stochastic systems", *Automatica*, Vol. 30, 75-93, 1994.
[10] G. Box and A. Luceno, *Statistical control by monitoring and feedback*, john Wiley, NY, 1997.
[11] L. Ljung, *System identification: Theory for the user*, Prentice-Hall, NJ, 1999.