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PERFORMANCE EVALUATION OF AN INDUSTRIAL MPC CONTROLLER

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Abstract: This paper presents an industrial case study of the performance evaluation of a multivariate MPC-based controller as implemented on a 6-output, 6-input industrial process with 6 measured disturbance variables that are used for feed forward control. The industrial unit is a Para-Xylene (PX) production process at Mitsuibishi's petrochemical complex in Mizushima, Japan. A generalized predictive controller-based MPC algorithm has been implemented on the PX process. Data from the PX unit before and after the MPC implementation is analyzed to obtain and compare several different measures of multivariate controller performance.

1. INTRODUCTION

The last decade has witnessed a growing interest by practitioners and academics alike in the field of controller performance monitoring (Harris, Harris and co-workers 1989-1999, Huang and Shah 1996-1999, Kozub 1996) . The basic idea in performance monitoring is to obtain a measure of 'performance' of a closed loop system from routine closed-loop output and input data. In short, the role of performance evaluation is to see if the controller is doing its job satisfactorily and if not, further analyze closed loop data with process information to diagnose the causes of poor performance.

Routine monitoring of controller performance ensures optimal operation of the regulatory control layers and the higher level advanced process control (APC) applications. Model predictive control (MPC) is currently the main vehicle for implementing the higher level APC layer. The APC algorithms include a class of model based controllers which compute future control actions by minimizing a performance objective function over a finite prediction horizon. This family of controllers is truly multivariate in nature and has the ability to run the process close to its limits. It is for the above reasons that MPC has been widely accepted by the process industry. Various commercial versions of MPC have become the norm in industry for processes where interactions are of foremost importance and constraints have to be taken into account. Most commercial MPC controllers also include a linear programming stage that deals with steady-state optimization and constraint management.

Several authors have proposed approaches for evaluation of the performance of multivariate controllers (see Harris et al., Huang and Shah 1996-1999, Shah et al., Ko and Edgar). This paper is concerned with the application of some of these methods towards performance evaluation of an industrial MPC controller. In this paper we adopt a graphical measure of multivariate controller performance. This is a generalization of the univariate impulse response (between the process output and the whitened disturbance variable) plot to the multivariate case, and defined as the 'Normalized Multivariate Impulse Response' plot. A particular form of this plot, that does not require knowledge of the process time-delay matrix, is used here.

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Such a plot provides a graphical measure of the multivariate controller performance in terms of settling time, decay rates etc. This graphical measure is compared with the multivariate minimum variance benchmark in which the interactor or the time delay matrix is first computed from the step-response model required for the design of the MPC controller. Another measure of multivariate performance is also explored in detail in this study: the use of the design performance as a benchmark. The design objective function based approach can be applied to constrained MPC type controllers and is therefore a practical measure. However, it does not tell you how close the performance is relative to the lowest achievable limits. In this respect the minimum variance-benchmarking index complements the objective function measure very well.

2. PROCESS DESCRIPTION

In order to achieve operational efficiency in terms of production costs, stable and reduced variance product composition and automated versus manual process operation, a multivariable model predictive controller was designed and implemented on the PX distillation unit at Mitsubishi Chemical Corporation's, Mizushima plant in Japan. The distillation unit of the PX plant consists of three columns where raw Xylene is separated into the main product, OX, and other byproducts. A schmatic of the process flow sheet is shown in Figure 1. Xylene feed and recycled Xylene from the isomerization section are mixed and fed to the light end column. In the light end column, the light components (C1-C5, toluene and benzene) are separated and the bottom products, composed of Xylene and 'heavies', (more than C9), are fed to the OX column. In the OX column, the OX and heavy components show up as the bottom products whereas mixed PX and Meta-Xylene are distillated to the overhead. The mixed Xylenes in the overhead are fed to the crystallization section. The OX and heavy components are fed to the OX purification column where the heavy components end up at the bottom and the pure OX, as a product, is distillated to the overhead. The heat furnace is used as a reboiler for the OX column, because high temperatures and significantly large heat duties are necessary for OX distillation. The separated light and heavy components are used as fuel to the heat furnace.

In the conventional operation of this unit, reboiler steam at the light end column, heat furnace fuel and the OX column were all operated manually to keep the reflux ratio and column operational. Ambient temperature and fuel composition changes are the main disturbances to this unit. These disturbances forced manual operation of the column, one of the consequences of which and resulted in high reflux ratio to keep product specification.

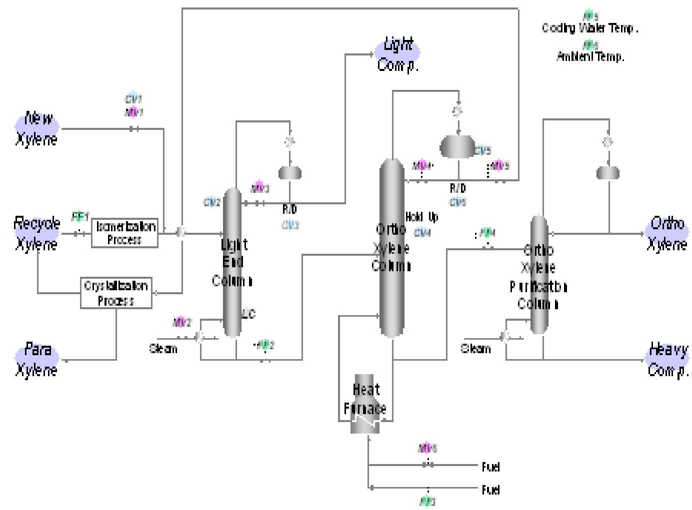

Fig. 1. *Process flow sheet of the Para-Xylene distillation unit*

3. MULTIVARIABLE MODEL PREDICTIVE CONTROLLER STRATEGY

A Multivariable model predictive controller software package based on the 'Hitachi PS21_IMPACT' controller was implemented on the PX unit. ARX models were identified from the plant input/output data and control adjustments are calculated based on the generalized predictive control algorithm to minimize the following cost function:

$$J = \kappa \sum_{j=N_1}^{N_2} (\hat{y}(t+j) - w(t+j))^2 + \lambda \sum_{k=0}^{N_u} \Delta u(t+k)^2 \quad (1)$$

where $\hat{y}(t+j)$ is j-step ahead prediction of the system output on data up to time t, N_1 and N_2 are the minimum and maximum costing horizons, N_u is the control horizon, κ and λ are the weights and $w(t)$ is the future reference.

A list of controlled, manipulated and disturbance variables and the corresponding weights(κ, λ) with the prediction horizons are given in Table.1. Note that in this table, CV1 and MV1 are identical. This is frequently done under MPC either to square the system or alternately to maximize the feed here, as is the case, and yet also be able to manipulate it, should circumstances dictate so, e.g., to prevent flooding. The implementation results of this GPC-based MPC control algorithm are shown in right hand column in Figure.2. The

Table 1. *Controller design parameters for the MPC-based multivariate objective function*

No.CV	Tag	Weight	Horizon
CV1	Xylene feed	5.0	20
CV2	Tray #5 temperature	2.5	100
CV3	Internal reflux ratio	0.05	100
CV4	OX Hold up	6.0	100
CV5	OX reflux drum level	0.3	100
CV6	OX reflux ratio	1.4	50
No.MV	Tag	Weight	Horizon
MV1	Xylene feed	35	3
MV2	Reboiler steam	200	3
MV3	Internal reflux	15	3
MV4	OX reflux	20	3
MV5	OX distillate	100	3
MV6	Fuel heat calorie	25	3

Table 2. *Disturbance Variables*

No.FF	Tag
FF1	Isomerization feed
FF2	OX column feed
FF3	Heat furnace fuel heat calorie residual
FF4	OX purification column feed
FF5	Cooling water temperature
FF6	Ambient temperature

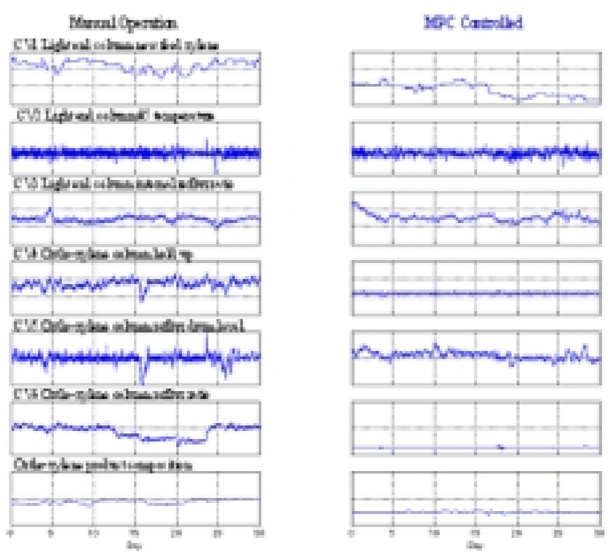

Fig. 2. *The result of MPC application for distillation unit of para-xylene plant*

left column shows the control results before the MPC was installed. The scales for the same CVs are the same.

4. MPC PERFORMANCE MONITORING, AN INDUSTRIAL APPLICATION

The procedure for multivariate performance monitoring in terms of the minimum variance benchmark can be summarized as follows:

- Given an open loop model, calculate the unitary interactor matrix for the multivariate process.
- Given routine closed loop operating data, compute the performance index by time series analysis via the MFCOR algorithm.

4.1 *Calculation of the unitary interactor matrix based on open loop model*

In order to calculate the unitary interactor matrix, we need to know the open loop process model (or at least the first few Markov matrices of the multivariate system) as *apriori* knowledge. The current open loop process model for PX MPC(IMPACT)(with two MVs and one CV out of service this time) is:

$$\begin{bmatrix} z^{-1} & 0 & 0 & 0 & 0 & 0 \\ s21 & s22 & s23 & 0 & s25 & 0 \\ s31 & s32 & s33 & 0 & s35 & 0 \\ 0 & 0 & 0 & 0 & s45 & 0 \\ s51 & s52 & 0 & s54 & s55 & s56 \\ 0 & 0 & 0 & 0.2z^{-1} & -0.1679z^{-1} & 0 \end{bmatrix}$$

where

$$s21 = \frac{-0.06809z^{-1} - 0.1408z^{-2}}{1 - 0.2845z^{-1} - 0.6746z^{-2}};$$
$$s22 = \frac{-0.06038z^{-1} + 0.2498z^{-2}}{1 - 1.69z^{-1} + 0.6978z^{-2}};$$
$$s23 = \frac{-0.02414z^{-1} - 0.266z^{-2}}{1 - 0.8188z^{-1} - 0.153z^{-2}};$$
$$s25 = \frac{-0.1297z^{-1} + 0.4256z^{-2}}{1 - 1.301z^{-1} + 0.3159z^{-2}};$$
$$s31 = \frac{-0.02498z^{-1} + 0.03939z^{-2}}{1 - 1.868z^{-1} + 0.8764z^{-2}};$$
$$s32 = \frac{0.1092z^{-1} - 0.1551z^{-2}}{1 - 1.873z^{-1} + 0.8796z^{-2}};$$
$$s33 = \frac{0.01148z^{-1} + 0.01025z^{-2}}{1 - 1.876z^{-1} + 0.8823z^{-2}};$$
$$s35 = \frac{-0.0408z^{-1} - 0.008103z^{-2}}{1 - 1.814z^{-1} + 0.8235z^{-2}};$$
$$s45 = \frac{-0.1968z^{-1}}{1 - 0.99z^{-1}}; \qquad s51 = \frac{-0.1464z^{-2}}{1 - 0.99z^{-1}};$$
$$s52 = \frac{0.34z^{-2}}{1 - 0.99z^{-1}}; \qquad s54 = \frac{-1.399z^{-2}}{1 - 0.99z^{-1}};$$
$$s55 = \frac{-0.4911z^{-2}}{1 - 0.99z^{-1}}; \qquad s56 = \frac{3.766z^{-2}}{1 - 0.99z^{-1}};$$

Then a unitary interactor matrix is factorized out as (Huang and Shah, 1999):

$$\begin{bmatrix} 0.05925z & 0.7234z & 0.4z & -0.5596z & 0 & 0 \\ 0.006454z & 0.4251z & -0.9003z & -0.0934z & 0 & 0 \\ -0.02356z & -0.3103z & -0.09755z & -0.4734z & 0 & 0.8183z \\ -0.03354z & -0.4417z & -0.1389z & -0.6739z & 0 & -0.5748z \\ -0.9974z & 0.06791z & 0.02491z & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & z^2 & 0 \end{bmatrix}$$

4.2 *Time series analysis of closed loop data via the MFCOR algorithm*

Prior to time series analysis of the data, it is necessary to perform certain treatment of closed loop data such as outlier removal, mean centering and auto scaling.

The closed loop data used for performance monitoring corresponding to PX MPC(IMPACT) on and off was available at 1 min sample rate with

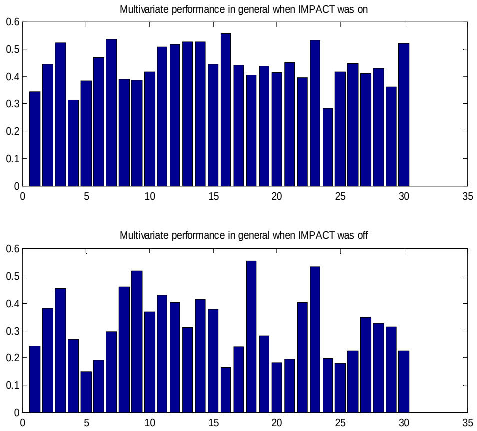

Fig. 3. *Multivariate performance assessment of MCC over 30 days(each bar indicates performance measure for 1 day)*

a length of 43200(30 days). It is assumed that the two data sets with and without IMPACT corresponded to similar periods of operation. To evaluate the daily performance, we used a moving window of 1440 data points without overlapping corresponding to each day to calculate the daily multivariate performance index (see Figure.3) as well as individual performance indices at different channels or for different outputs. The definition of multi-variate performance index and detailed MFCOR alogrithm with interactor matrix filtering can be refered to the book by (Huang and Shah 1999). Bar charts corresponding to the 'on' and 'off' status of the IMPACT controller were generated. It is clearly seen that a significant improvement in performance resulted after the IMPACT controller was implemented. In Figure.4, the overall performance index and individual performance indices over a 30-day period are displayed. A significant improvement in overall performance(>300%) is clear from this figure. It is noticed as well that the performance of a few controlled variables improved significantly while the performance of others degraded as a result of different controller weightings. It is to be expected that performance in some loops would improve at the expense of reduced performance in other loops.

4.3 *Performance evaluation via alternative methods*

To make sure that the IMPACT MPC controller has been able to achieve overall control objectives, the objective function based evaluation method (Patwardhan,1998; Shah et al., 2001) was applied in this industrial application.

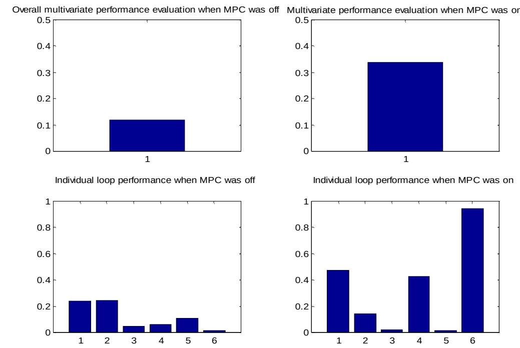

Fig. 4. *Overall as well as individual loop performance assessment of MCC over 30 days*

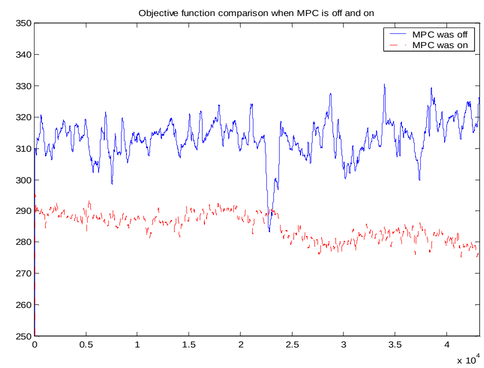

Fig. 5. *Objective function comparison (based the moving horizons and weights of CV and MV data)*

4.3.1. *Multivariate Objective function comparison*

The objective of this MPC controller is to minimize the quadratic objective function, as specified in Equation 1 and Table.1. In order to demonstrate that the current MPC controller is working effectively towards this objective, we calculated the value of this objective function corresponding to the state when MPC was 'on' and 'off'. As shown in Figure 5, the objective function corresponding to MPC-on shows a significant decrease in the quadratic cost function compared with that corresponding to MPC-off. If we computed contributions by different controlled variables as shown in Figure 6, large decreases in channels corresponding to CV1, CV4 and CV6 are obvious as a result of higher weighting for these variables as indicated in Table 1.

4.3.2. *Spectral analysis* Another objective of MPC is to reduce the interaction between different loops. Cross-spectrum/coherency analysis is a useful tool to assess the interaction behavior between different control loops. In this industrial application, the coherency of six control variables during the IMPACT-ON versus IMPACT-OFF periods were computed and compared with each

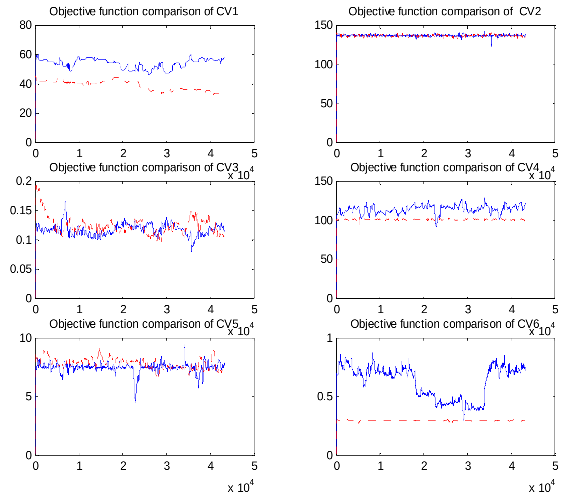

Fig. 6. *Objective functions contributed by different outputs*

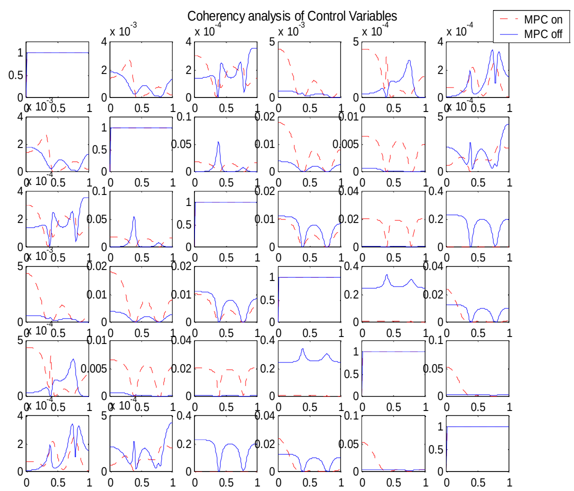

Fig. 7. *Coherency analysis of control variables*

other using the "cohere" function in MATLAB Signal Processing Toolbox. Figure 7 shows this plot where off-diagonal terms represent the coherency between the corresponding control variables. As shown in Figure 7, all off-diagonal terms in the frequency domain are far below 1 which indicates that interactions between different loops are small. In particular, the magnitudes of some off-diagonal terms (see coherency plot of "CV3 versus CV6" and "CV4 versus CV5") decrease significantly as a result of MPC application, which indicates that the MPC controller is effective in interaction reduction.

4.3.3. *Normalized multivariate impulse response* An impulse response curve represents the dynamic relationship between the whitened disturbance and the process output. In the univariate case, the first "d" impulse response coefficients are feedback control invariant, where "d" is the process time delay. Therefore, if the loop is under minimum variance control, the impulse response coefficients should be zero after "d-1" lags. The Normalized Multivariate Impulse Response (NMIR) curve reflects this idea for a multivariate controlled system. The first "d" NMIR coefficients are feedback controller invariant, where "d" is the order of the interactor matrix. If the loop is under multivariate minimum variance control, then the NMIR coefficients should delay to zero after "d-1" lags. The sum of squares under NMIR curve is equivalent to the sum of the trace of the covariance matrix of the data. If output variance is

$$Y_t = E_0 a_t + E_1 a_{t-1} + \ldots + E_{d-1} a_{t-d+1} + E_d a_{t-d} + \ldots \tag{2}$$

and the filtered output variance is:

$$\tilde{Y}_t = q^{-d} D(F_0 a_t + F_1 a_{t-1} + \ldots + F_{d-1} a_{t-d+1} + F_d a_{t-d} + \ldots) \tag{3}$$

we have:

$$E(Y_t^T Y_t) = E(\tilde{Y}_t^T \tilde{Y}_t) = trace(F_0 \sum_a F_0^T) + trace(F_1 \sum_a F_1^T) + \ldots, \tag{4}$$

where the first NMIR coefficient is given by $\sqrt{trace(F_0 \sum_0 F_0^T)}$ and the second NMIR coefficient is given by $\sqrt{trace(F_1 \sum_a F_1^T)}$, and so on. The multivariate performance index is then equal to the ratio of the sum of the squares of the first "d" NMIR coefficients to the sum of all NMIR coefficients.

The NMIR outlined above requires *apriori* knowledge of the interactor matrix. In this specific application, we compute the NMIR of the interactor filtered output from knowledge of the computed interactor matrix. As a complement, a similar normalized multivariate impulse curve without interactor filtering is also computed to serve a similar purpose. In this calculation, the $NMIR_{wof}$ coefficients are given by the E-matrices$(E_0, E_1, \ldots)$ instead of the F-matrices$(F_0, F_1, \ldots)$. The rationale for using the $NMIR_{wof}$ is that the two calculations are asymptotically equal (see Shah et al. 2001 for further details):

$$\lim_{t\to\infty} (trace(E_0 \sum_a E_0^T) + trace(E_1 \sum_a E_1^T) + \ldots) = (trace(F_0 \sum_a F_0^T) + trace(F_1 \sum_a F_1^T) + \ldots)$$

The result is clearly shown in Figure 8, which complies with the theoretical derivation for this specific industrial application. The $NMIR_{wof}$ curve corresponding to the MPC "on" case decays quickly, which again leads to the conclusion that

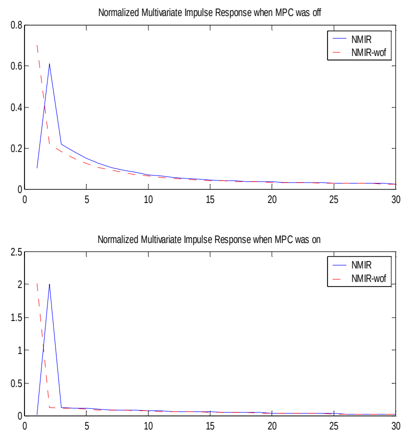

Fig. 8. Normalized Multivariate Impulse Response

the MPC controller improves the performance of multivariate controlled system significantly.

5. CONCLUDING REMARKS

In this application, automatic control was achieved and operator intervention were reduced by 87%. The OX column operation was stabilized and reflux ratio was reduced. The latter improvement resulted in significant reduction of fuel consumption. Finally stable operation of OX product composition was achieved. Several measures of multivariate controller performance monitoring have been introduced and applied to performance evaluation of the Hitachi IMPACT controller on the PX Distillation Process at Mitsubishi's Mizushima Petrochemical Complex. It is shown that routine monitoring of MPC application can ensure that corrective measures will be taken when control degrades and finally ensure a good and optimal control. Results by different measures indicate significant improvement from the implementation of the IMPACT MPC controller. We hope this application of the new multivariate performance assessment technology will advocate more extensive and intelligent use of performance assessment technology and eventually lead to automated monitoring of the design, tuning and upgrading of the control loops.

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