

Multi-loop Internal Model Controller Design Based on a Dynamic PLS Framework^{*}

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Abstract In this paper, a multi-loop internal model control (IMC) scheme in conjunction with feed-forward strategy based on the dynamic partial least squares (DyPLS) framework is proposed. Unlike the traditional methods to decouple multi-input multi-output (MIMO) systems, the DyPLS framework automatically decomposes the MIMO process into a multi-loop system in the PLS subspace in the modeling stage. The dynamic filters with identical structure are used to build the dynamic PLS model, which retains the orthogonality among the latent variables. To address the model mismatch problem, an off-line least squares method is applied to obtain a set of optimal filter parameters in each latent space. Without losing the merits of model-based control, a simple and easy-tuned IMC structure is readily carried over to the dynamic PLS control framework. In addition, by projecting the measurable disturbance into the latent subspace, a multi-loop feed-forward control is yielded to achieve better performance for disturbance rejection. Simulation results of a distillation column are used to further demonstrate this new strategy outperforms conventional control schemes in servo behavior and disturbance rejection.

Keywords internal model controller, partial least squares, latent subspace, servo behavior, disturbance rejection

1 INTRODUCTION

In the past decades, Partial Least Square (PLS) as a multivariable chemometric tool has been extensively used in chemical industrials for process monitoring and modeling such as fault detection and diagnosis, soft sensing, *etc.* However, little attention was paid to apply this method to the controller design. Kaspar and Ray [1] first introduced a special proportion integral derivative (PID) control scheme by using the loading matrices derived from a PLS model as compensators for the plant. In that way, the complex multi-input multi-output (MIMO) control problem was reduced to a simple multi-loop control system in the subspace and the advantages of automatic decoupling and efficient loop pairings enabled separated and independent controller designs. In addition, Patwardhan *et al.* [2] developed methods of implementing an input-constrained, nonlinear and model-predictive controller in latent spaces within PLS-based Hammerstein and Wiener framework. An adaptive multi-loop PID algorithm was proposed based on a new integrated structure, which connects the PLS gain matrix with linear dynamic model [3]. By instantaneously updating the PLS model at each sampling time, Chen and Cheng extended this linear integrated structure to nonlinear processes [4]. With regard to large scale manufacturing process, Song *et al.* [5] effectively combined model predictive control (MPC) with PLS modeling method to achieve desired product quality with optimal costs and time. As to batch processes control, MacGregor *et al.* [6, 7] presented a multivariate empirical model predictive control strategy for the

control of batch product quality by using latent variables models, wherein trajectory tracking and disturbance rejection were investigated. Although some developed control strategy had successfully merged into the modified PLS framework, there are two aspects needed to be further taken into account: (1) Although the dynamic PLS based PID control scheme is fully exploited by Kaspar, *etc.*, it did not alter the nature of conventional PID, being poor in controlling systems with time delay. (2) Despite that MPC algorithm has replaced the PID controller in the PLS-based control framework to handle constrained control, the robustness analysis of such control system is not of ease and sometimes even impossible.

For model-based method, Internal Model Control (IMC) is a well known advanced control strategy capable of perfectly handling the controlled processes with serious time-delay. At early time, Morari, *etc.* had deeply investigated the underlying mechanism of internal model structure and pointed out that conventional controllers in feedback control can be generally reconstructed to yield IMC [8, 9]. For the systems open-loop stable, Wang *et al.* [10] developed a decoupling internal model controller with stability to achieve satisfactory control performance in a multivariable multi-delay plant by including some time delays and non-minimum phase zeros in open-loop systems. For unstable processes, a modified IMC structure was proposed by Tan *et al.* with an advantage that set-point tracking and disturbance rejection could be designed separately [11]. Henson *et al.* [12, 13], Hunt and Sbarbaro [14] proposed methods for the nonlinear IMC design based on feed-forward Neural

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Network Model, which yields a better performance than conventional PID control in two highly-nonlinear processes [12–14]. Unfortunately, the methods mentioned above usually require detailed process models, which are hard to obtain and may lead to complex control structures that are unable to adjust in the field.

To improve the multi-loop control performance and make it feasible in the field, a new multi-loop IMC strategy based on dynamic PLS model is investigated here. The next section provides a brief introduction to the dynamic PLS modeling. The main topic of the paper involving building the IMC on a dynamic PLS framework is then presented. Subsequently, a new and simple method to design multivariable feed-forward control scheme within the PLS framework is developed to improve the performance in rejecting disturbance. Finally simulation results for a distillation column are used to demonstrate the effectiveness of the proposed method.

2 PLS MODELING

2.1 Dynamic PLS modeling

Partial Least Squares(PLS), also known as Projection to Latent Structure, is a dimensionality reduction technique for maximizing the covariance between the predictor matrix(independent) and the predicted(dependent)matrix for each component of the reduced space [15, 16]. Suppose $\mathbf{X} = (x_{ij})_{n \times m}$ represents the input data set and $\mathbf{Y} = (y_{ij})_{n \times s}$ output data set where n is the total number of observations, m the number of predictor variables, and s the number of predicted variables. The general PLS technique consists of two sub-models-outer model and inner model. As for outer model, the linear model is built by decomposing matrices $\mathbf{X}$ and $\mathbf{Y}$ into bilinear terms,

$$\mathbf{X} - \mathbf{E}^* = \sum_{i=1}^a \mathbf{t}_i \mathbf{p}_i^T = \mathbf{TP}^T \quad (1)$$

$$\mathbf{Y} - \mathbf{F}^* = \sum_{i=1}^a \mathbf{u}_i \mathbf{q}_i^T = \mathbf{UQ}^T \quad (2)$$

where a is the number of latent variables that can be determined by cross-validation approach. $\mathbf{p}_i$ and $\mathbf{q}_i$ are latent loading vectors of the i th PLS component, and $\mathbf{t}_i$ and $\mathbf{u}_i$ are the orthogonal vectors which are projections from original space. $\mathbf{E}^*$ and $\mathbf{F}^*$ are residual matrices in $\mathbf{X}$ and $\mathbf{Y}$ respectively.

In inner model, the regression coefficient b_i which approximates the algebraic relationship between latent variables is obtained by least squares method. Combining the inner model and outer model leads to the final model given in Eq. (5).

$$\hat{\mathbf{u}}_i = b_i \hat{\mathbf{t}}_i + \mathbf{r}_i \quad (3)$$

$$b_i = \frac{\mathbf{u}_i^T \mathbf{t}_i}{\mathbf{t}_i^T \mathbf{t}_i} \quad (4)$$

$$\mathbf{Y} - \hat{\mathbf{F}} = \sum_{i=1}^a b_i \mathbf{t}_i \mathbf{q}_i^T = \mathbf{TBQ}^T \quad (5)$$

$\hat{\mathbf{F}}$ is the residual matrix in the final PLS model. The overall implementation of PLS modeling is generally accomplished by means of numerical approach, which provides iterative solutions to its parameters. In this paper, the modified PLS algorithm proposed by Qin [16] is used to build a linear PLS model.

Nevertheless, because the standard PLS approach is poor at coping with the dynamic relationships in the process, two widely-used dynamic PLS frameworks are discussed here. Ricker [17] proposed a PLS Finite Impulse Response (FIR) model to interpret the time-series correlation in the input data block by including certain amount of lagged values of input variables in the data matrix. Qin and MacAvoy [18] produced a parsimonious multivariable autoregressive with exogenous (ARX) model *via* encompassing lagged values of both input variables and output variables in $\mathbf{X}$ block. Unlike forementioned approaches, Kaspar and Ray revisited the dynamic modeling in a new fashion. By imposing the dynamic filter on the input data set $\mathbf{X}$ before modeling procedure, they developed an algebraic model between the transformed input variables and the output variables [19].

The Kaspar/Ray method is chosen in our work to effectively avoid the dimension expansion, as well as endow input variables with explicit physical explanation, which allows a simple model adaptation for control system design. It is worthy to note that filter structure may influence the accuracy of the final model in a direct way. In this paper, the dynamic transfer function is estimated by pre-acquiring preliminary knowledge of the dominant time scale in processes. Consider the general structures of chemical processes are dominated by first order plus pure delay system, the dynamic filter can be selected as $e^{-\tau s} / (Ts + 1)$ where parameters T and τ can be optimized to make sure that the resulting models are matched with the plant after incorporating such dynamic filters [1].

It has been verified that dynamic filter can be moved into PLS inner model to build up the control framework [19]. Denoting dynamic transformation by $\mathbf{H}(\cdot)$, the transformed input data $\tilde{\mathbf{X}}$ is given as,

$$\tilde{\mathbf{X}} = \mathbf{H}(\mathbf{X}) \quad (6)$$

The mathematical term to express this modified dynamic PLS model is given in Eq. (7).

$$\mathbf{Y} - \mathbf{F} = \mathbf{H}(\tilde{\mathbf{T}}) \mathbf{BQ}^T \quad (7)$$

In order to cover as much dynamics as possible inherent in the system, the filters doing the input transformation may select in different forms. However, the variety in the structure of filters will result in the loss of the orthogonality among $\mathbf{t}_i$ and $\mathbf{w}_i$. As is stated in Kaspar's work, the degree of departure from orthogonality depends on the difference between the dynamic transformations. An explicit proof is presented here to

better understand the mechanism. For brevity, two decomposition procedures are provided to show the relationship between the first latent score $\mathbf{t}_1$ and the second one $\mathbf{t}_2$.

Assume the optimal filter for the first component is fixed, the first input score is derived as

$$\begin{aligned}\tilde{\mathbf{X}}_0 &= \mathbf{H}_1(\mathbf{X}_0) \\ \mathbf{t}_1 &= \mathbf{H}_1(\mathbf{X}_0)\mathbf{w}_1 \\ \mathbf{t}_1 &= \mathbf{H}_1(\tilde{\mathbf{t}}_1) = \mathbf{H}_1(\mathbf{X}_0\mathbf{w}_1)\end{aligned}\quad (8)$$

The second latent variable is obtained as follows:

$$\begin{aligned}\mathbf{X}_1 &= \mathbf{X}_0 - \tilde{\mathbf{t}}_1 \mathbf{p}_1^T \\ \tilde{\mathbf{X}}_1 &= \mathbf{H}_2(\mathbf{X}_1) \\ \mathbf{t}_2 &= \mathbf{H}_2(\mathbf{X}_1)\mathbf{w}_2\end{aligned}\quad (9)$$

and the orthogonality between $\mathbf{t}_1$ and $\mathbf{t}_2$ is:

$$\begin{aligned}\mathbf{t}_1^T \mathbf{t}_2 &= \mathbf{t}_1^T \mathbf{H}_2(\mathbf{X}_1)\mathbf{w}_2 = \mathbf{t}_1^T \mathbf{H}_2(\mathbf{X}_0 - \tilde{\mathbf{t}}_1 \mathbf{p}_1^T)\mathbf{w}_2 \\ &= \mathbf{t}_1^T \left[\mathbf{H}_2(\mathbf{X}_0) - \mathbf{H}_2(\tilde{\mathbf{t}}_1) \frac{\mathbf{t}_1^T \mathbf{H}_1(\mathbf{X}_0)}{\mathbf{t}_1^T \mathbf{t}_1} \right] \mathbf{w}_2 \\ &= \mathbf{t}_1^T [\mathbf{H}_2(\mathbf{X}_0) - \mathbf{H}_1(\mathbf{X}_0)] \mathbf{w}_2\end{aligned}\quad (10)$$

It is apparent that the two latent scores are orthogonal only if the dynamic filter forms are chosen the same. Loss of the orthogonality within control variables may pose a problem in independently regulating the system, since tuning parameters of one loop potentially has impact on others which eventually compromises the final performance. Therefore, in this paper, the optimal filters with identical forms in each subspace are applied to achieve satisfactory control performance without sacrificing mutual independence.

2.2 Filter structure identification

As the pivotal factor in the DyPLS model, the filter structure has direct impact on the resemblance between the model and the plant. Hence, an optimal objective is used to make the DyPLS output as close as possible to the plant,

$$\min J = \frac{1}{2} \sum_{t=1}^n [\mathbf{Y}(t) - \mathbf{Y}^{\text{pls}}(t)]^T \boldsymbol{\Gamma} [\mathbf{Y}(t) - \mathbf{Y}^{\text{pls}}(t)] \quad (11)$$

By multiplying $(\mathbf{Q}^T)^+$ on the left side and $\mathbf{Q}^+$ on the right side, the optimal objective in the latent subspace is obtained:

$$\min \tilde{J} = \frac{1}{2} \sum_{t=1}^n [\mathbf{U}(t) - \mathbf{U}^{\text{pls}}(t)]^T \boldsymbol{\Gamma} [\mathbf{U}(t) - \mathbf{U}^{\text{pls}}(t)] \quad (12)$$

Choosing $\boldsymbol{\Gamma} = \mathbf{I}$, $\mathbf{I}$ is an identity matrix, the above formulation can be represented as

$$\min \tilde{J} = \frac{1}{2} \sum_{t=1}^n \sum_{a=1}^A \|u_a(t) - u_a^{\text{pls}}(t)\|^2$$

$$\begin{aligned}&= \frac{1}{2} \sum_{a=1}^A \sum_{t=1}^n \|u_a(t) - u_a^{\text{pls}}(t)\|^2 \\ &= \min \tilde{J}_1 + \min \tilde{J}_2 + \cdots + \min \tilde{J}_a + \cdots + \min \tilde{J}_A\end{aligned}\quad (13)$$

where $\tilde{J}_a = 1/2 (\mathbf{U}_a - \mathbf{U}_a^{\text{pls}})^T (\mathbf{U}_a - \mathbf{U}_a^{\text{pls}})$. Whence, the overall optimal objective is divided into several sub-objectives in the DyPLS subspace. $\mathbf{U}_a$ and $\mathbf{U}_a^{\text{pls}}$ are the vectors corresponding to the plant and model output of the latent space respectively.

$$\begin{aligned}\mathbf{U}_a &= [u_a(1)u_a(2) \cdots u_a(n)]^T \\ \mathbf{U}_a^{\text{pls}} &= [u_a^{\text{pls}}(1)u_a^{\text{pls}}(2) \cdots u_a^{\text{pls}}(n)]^T\end{aligned}\quad (14)$$

Without loss of generality, the filter structure in the latent subspace can be described as

$$\begin{aligned}A(q^{-1})u_a^{\text{pls}}(t) &= \tilde{b}_a q^{-d_a} B(q^{-1})t_a(t) + e_a(t) \\ A(q^{-1}) &= 1 + a_1 q^{-1} + \cdots + a_n q^{-n} \\ B(q^{-1}) &= b_0 + b_1 q^{-1} + \cdots + b_m q^{-m}; \quad b_0 \neq 0.\end{aligned}\quad (15)$$

where $\{t_a^{\text{pls}}\}$, $\{u_a^{\text{pls}}\}$ denote the input and output latent sequences, respectively, and $A(q^{-1})$, $B(q^{-1})$ are polynomial functions with filter parameters $\{a_i\}$, $\{b_j\}$, $\tilde{b}_a$, $i=1, \dots, n$; $j=1, \dots, m$ to be estimated. d_a represents the time delay in the latent subspace, while $e_a(t)$ is the model error.

In this case, a standard least squares method is used to obtain an optimal set of filter parameters, which minimize the mismatch between the DyPLS model and the plant.

3 INTERNAL MODEL CONTROLLER DESIGN

3.1 Dynamic PLS control framework

In today's chemical process, it becomes more and more difficult, sometimes even impossible, to implement control rules on a principle-based model in that controlled plants are always extremely complex MIMO systems with strong coupling and highly nonlinear features. For that reason, the data-based approach, which requires less process knowledge has its advantage in easy-modeling and may potentially achieve better performance.

Kaspar and Ray first attempted to build the concept of controller design on the PLS inner model by employing the loading vectors $\mathbf{P}$ as pre-compensator and $\mathbf{Q}$ as post-compensator for the actual plant. And such control scheme is illustrated in Fig 1.

$\mathbf{W}_x$ and $\mathbf{W}_y$ are diagonal scaling matrices. $\mathbf{G}_c$, $\mathbf{G}_p$ and $\mathbf{G}_d$ are the transfer function matrices of the

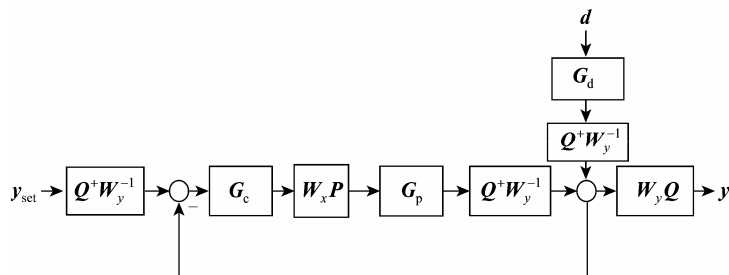


Figure 1 Block diagram of control scheme based on DyPLS framework

controller in the subspace, the controlled plant and disturbances, respectively. $\mathbf{Q}$ is the loading matrix for the output data block, and $\mathbf{Q}^+$ is an appropriate inverse of $\mathbf{Q}$. When the number of output variables is equal to output scores, $\mathbf{Q}^+$ can be replaced by $\mathbf{Q}^{-1}$; if the number of output variables is less than latent variables, the appropriate inverse is right inverse, $\mathbf{Q}^+ = \mathbf{Q}^T (\mathbf{Q}\mathbf{Q}^T)^{-1}$; otherwise, the inverse is left inverse $\mathbf{Q}^+ = (\mathbf{Q}^T \mathbf{Q})^{-1} \mathbf{Q}^T$.

The block diagram shows that the significant dissimilarity between this new control scheme and the traditional one is that the control action is performed on score variables rather than physical manipulated variables. And such control scheme has two merits: (1) It enables the conversion from designing complex strong-coupled MIMO control system to simply controlling several independent single-input single-output (SISO) loops; (2) Infeasible set points will not be retained after going through the projection into latent space, which enhances the robustness of the control system.

3.2 Internal model controller design in latent spaces

It has been justified that the dynamic filter imposed on the input variables can be equally transferred into the PLS inner relation since this change lies in its intrinsic linearity. Thus, the dynamic relationship between input scores $\mathbf{T}$ and output scores $\mathbf{U}$ can be reasonably interpreted by the transformed PLS inner model $\mathbf{BH}$, where $\mathbf{B}$ is the regression coefficient matrix and $\mathbf{H}$ is the diagonal matrix containing dynamic filters. In addition, if there is no mismatch between the plant and PLS model, any control law implemented on the compensated plant $\mathbf{P}\mathbf{W}_x \mathbf{G}_p \mathbf{W}_y^{-1} \mathbf{Q}^+$, which is defined on a basis of loading vectors, can be applied equally to the PLS inner model $\mathbf{BH}$. However, often is the case that imperfection occurs and strongly influences the control performance while building a PLS model. It is necessary to opt for a proper control strategy which is intrinsically capable of narrowing the gap between the model and plant. Therefore, a PLS based IMC scheme is proposed and investigated here to demonstrate how the internal model controller is built into the latent spaces. The connection between the PLS inner model and the controller design is established by laying every single control loop into each subspace.

With regard to controller design, the dynamic PLS inner model $\mathbf{BH}$ acts as the estimated model $\hat{\mathbf{G}}_p(s)$ in IMC control scheme. The dynamic relation among i th pair of latent variables is given as

$$\mathbf{u}_i = b_i h_i \mathbf{t}_i \quad (16)$$

where $\mathbf{u}_i$, b_i , $\mathbf{t}_i$ represent the i th output score vector, regression coefficient, and input score vector, respectively. h_i is the i th diagonal element in the transfer function matrix $\mathbf{H}$. Thus, the estimated model $\hat{\mathbf{G}}_{pi}(s)$ in the i th control loop is $b_i h_i$. In the light of IMC design procedure, the estimated model can be factorized as

$$\hat{\mathbf{G}}_{pi}(s) = \hat{\mathbf{G}}_{pi-} \hat{\mathbf{G}}_{pi+} = b_i h_i = b_i h_{i-} h_{i+} \quad (17)$$

And the internal model controller in the i th control loop is

$$\hat{\mathbf{G}}_{ci}^*(s) = \frac{1}{\hat{\mathbf{G}}_{pi-}} f = \frac{1}{b_i h_{i-}} f \quad (18)$$

$$f = \frac{1}{(T_i s + 1)^r} \quad (19)$$

Unlike the conventional IMC multi-loop design that tightly depends on the structure of practical process, the approach investigated here decomposes MIMO control system into a couple of SISO loops where the traditional IMC strategy can be easily applied without rigorous structure. To explain the design work in a more straightforward fashion, the detail of IMC loop in one PLS subspace is demonstrated in Fig. 2. It should be noted that $\hat{\mathbf{G}}_{pi}(s)$ represents the transfer function of the compensated plant ($\mathbf{P}\mathbf{W}_x \mathbf{G}_p \mathbf{W}_y^{-1} \mathbf{Q}^+$) in i th loop.

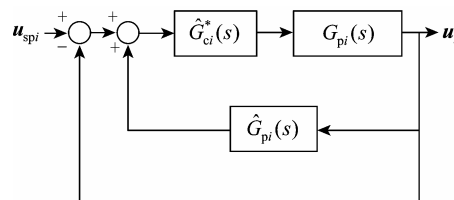


Figure 2 IMC scheme block within PLS inner model

3.3 DyPLS-based feed-forward controller design

Feed-forward control strategy is an effective and well known method in rejecting disturbances which

can be measured in the process. Nevertheless, when this approach applies to MIMO case, it poses an extreme difficulty in choosing loop pairings to conduct the feed-forward control, because the disturbances added to the plant always have intense interactions on each other as well as the process outputs.

Similar to the widely used method RGA (relative gain analysis), which is considered as an effective guidelines for the loop pairings, Stanley *et al.* [20] proposed a new measurement named RDG(relative disturbance gain) to determine the input-output loop pairings for perfect control by including the disturbance information. However, the effectiveness of this method still counts on the accuracy of the physical model, especially its steady-state gain. For the new control scheme introduced here, it is convenient to project the disturbance input into the latent space so that the pairing work can be automatically done, since the control scheme based on DyPLS model has been already established. After the projection, the MIMO system with multivariable disturbance is reduced to several approximately independent SISO systems in the subspace with single “disturbance” for each loop. The following is the mathematical formulation of this projection along with two types of feed-forward controller design based on the steady state and dynamic behavior, respectively.

(1) Steady state case. $\tilde{\mathbf{G}}_d$ is the projection to the latent space, while $\mathbf{G}_d(0)$ represents the steady state of the disturbance in the original space. $\tilde{G}_{di}$, G_{ffi} and $\hat{G}_{pi}(0)$ are the magnitudes of the disturbance, feed-forward controller and the model in i th loop, respectively.

$$\tilde{\mathbf{G}}_d = \mathbf{Q}^+ \mathbf{W}_y^{-1} \mathbf{G}_d(0), \quad G_{\text{ffi}} = -\frac{\tilde{G}_{di}}{\hat{G}_{vi}(0)} \quad (20)$$

(2) Dynamic case. $\tilde{\mathbf{G}}_d(s)$, $\mathbf{G}_d(s)$, $G_{ffi}(s)$, $\tilde{G}_{di}(s)$ and $\hat{G}_{di}(s)$ are the transfer functions accordingly.

$$\tilde{\mathbf{G}}_d(s) = \mathbf{Q}^+ \mathbf{W}_y^{-1} \mathbf{G}_d(s), \quad G_{ffi}(s) = -\frac{\tilde{G}_{di}(s)}{\hat{G}_{pi}(s)} \quad (21)$$

To explicitly highlight the feed-forward role in the overall control scheme, the feedback controller is simplified by G_{fci} as shown in Fig. 3.

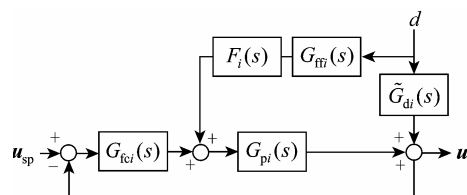


Figure 3 Feed-forward controller of one loop in the latent space

In the presence of model-plant mismatch, $F_i(s)$ is the first order filter with unit magnitude chosen to ensure smooth transition for the manipulated variables as well as zero offset in the steady state. If the DyPLS model has a perfect match with the actual plant, the feed-forward compensator is able to cancel the disturbance completely. With addition of the feed-forward scheme, an integrated control strategy is illustrated in Fig. 4.

4 EXAMPLE

In this section, a pilot-scale distillation column, which was developed by Ogunnaike *et al.* [21, 22] is used here to demonstrate the advantages of proposed control strategy in achieving good performance for multivariable process with multiple pure delay.

$$G_n(s) =$$

$$\begin{array}{ccc} \frac{0.66e^{-2.6s}}{6.7s+1} & \frac{-0.061e^{-3.5s}}{8.64s+1} & \frac{-0.0049e^{-s}}{9.06s+1} \\ \frac{1.11e^{-6.5s}}{3.25s+1} & \frac{-2.36e^{-3s}}{5.0s+1} & \frac{-0.012e^{-1.2s}}{7.09s+1} \\ \frac{-34.68e^{-9.2s}}{8.15s+1} & \frac{46.2e^{-9.4s}}{10.9s+1} & \frac{0.87(11.61s+1)e^{-s}}{(3.89s+1)(18.8s+1)} \end{array}$$

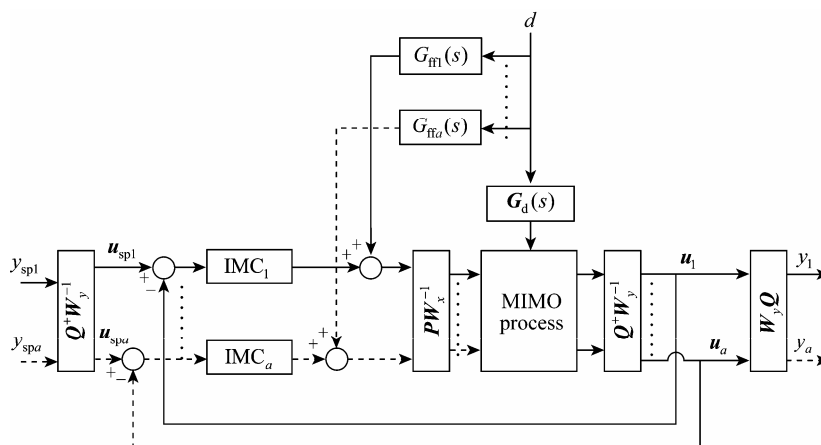


Figure 4 Multi-loop IMC scheme with feed-forward compensators based on DyPLS model

$$G_d(s) = \begin{bmatrix} \frac{0.14e^{-12s}}{6.2s+1} & \frac{-0.0011(26.32s+1)e^{-2.66s}}{(7.85s+1)(14.63s+1)} \\ \frac{0.53e^{-10.5s}}{6.9s+1} & \frac{-0.0032(19.62s+1)e^{-3.44s}}{(7.29s+1)(8.94s+1)} \\ \frac{-11.54e^{-0.6s}}{7.01s+1} & \frac{0.32e^{-2.6s}}{7.76s+1} \end{bmatrix}$$

Three enforcing pseudorandom signals ranging from -0.02 to $+0.02$, -0.02 to $+0.02$ and -2 to $+2$ respectively, are applied to exciting the system and generating data for PLS modeling. The parameters of the filter $H(s)$ are optimized and the results are shown as follows,

$$BH(s) = \begin{bmatrix} \frac{1.3394e^{-2s}}{7.935s+1} & & \\ & \frac{0.4936e^{-2s}}{7.935s+1} & \\ & & \frac{0.3937e^{-2s}}{7.935s+1} \end{bmatrix}$$

The Ogunnaike Ray control (ORC) method which Ogunnaike and Ray applied in their work [21], is rebuilt here to compare our work with theirs with respect to the servo performance and disturbance rejection. It should be mentioned that the effectiveness of ORC method highly depends on the detailed knowl-

edge and accurate physical model of the process. In contrary, the method proposed here does not need a strictly perfect model but can achieve similarly good results and in some aspects, even better performance than ORC method. The controller parameters used are summarized in Table 1. Note that the controller parameters used in all test cases are identical.

Table 1 Controller parameters summary: ORC system

Method	Overhead		Sidestream		Tray 19 [#] temp.	
	K_{P1}	K_{I1}	K_{P2}	K_{I2}	K_{P3}	K_{I3}
ORC	1.20	0.4	-1.5	1.07	1.20	0.667
Kaspar/Ray	0.58	0.12	0.65	0.34	1.16	0.188

Method	Overhead		Sidestream		Tray 19 [#] temp.	
	T_{f1}	r_1	T_{f2}	r_2	T_{f3}	r_3
DyPLS IMC	5	1	5	1	5	1
DyPLS IMC+dynamic FF	5	1	5	1	5	1

Note: T_{fi} and r_i are the parameters of the filter in the IMC, $i = 1, 2, 3$; K_{Pi} and K_{Ii} are the proportion and integral parameters in PI controllers.

Servo behavior Figs. 5 and 6 are provided to demonstrate the tracking performance to a step change of -0.05 units in y_1 (the overhead composition) and -0.08 units in y_2 (the sidestream composition) under the proposed scheme, ORC scheme. The current work

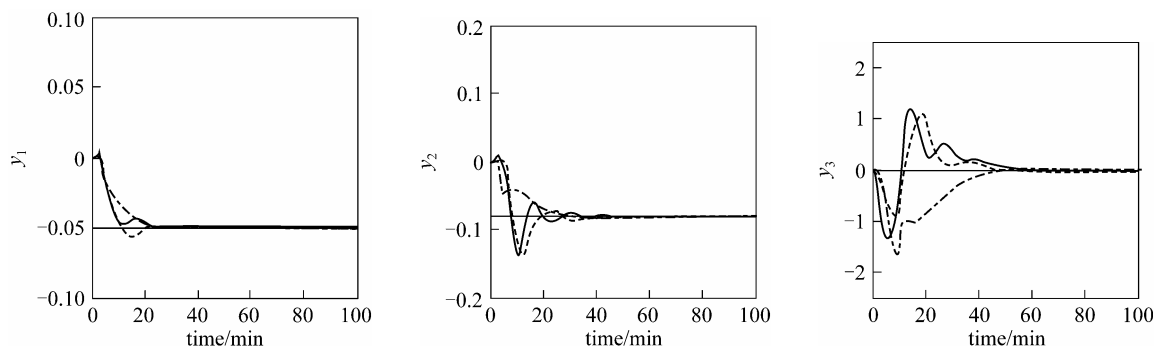


Figure 5 Column response to set point changes of -0.05 in y_1 and -0.08 in y_2
— DyPLS based IMC; ---- ORC strategy; ---- Kaspar/Ray method

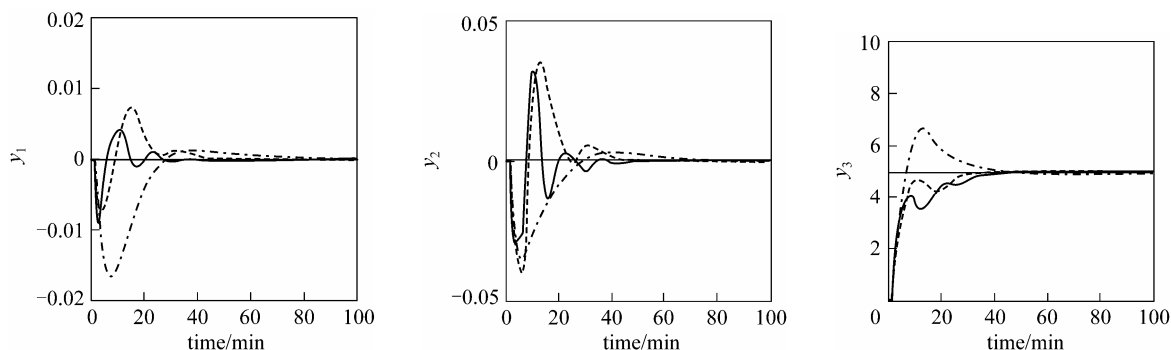


Figure 6 Column response to a set point change of $+5$ in y_3
— DyPLS based IMC; ---- ORC strategy; ---- Kaspar/Ray method

is also compared to the results that were presented by Kaspar and Ray, who adopted the PI controller based on DyPLS model with different filters.

As seen in Fig. 5, the first controlled variable y_1 approaches the set point more rapidly by using the proposed method than ORC method, while the setting time for the second and third outputs is quite similar to ORC.

Figure 6 shows the response to a step change of +5.0 in y_3 (Tray 19[#] temperature). It is evident that the response of y_1 exhibits better servo performance with less setting time than that of ORC and Kaspar/Ray, in which roughly 40 min was spent to reach the set point, while in our work only 20 min is needed. For the response of y_2 , it is quite similar to that of ORC method but faster than that of Kaspar/Ray. Because the requirement for regulating the third output y_3 (Tray 19[#]

temperature) is not as tight as y_1 and y_2 , more emphasis had been put on the first two outputs, resulting in the sluggish performance in y_3 .

Disturbance rejection Figs. 7–10 show the responses to step changes of +0.2 in d_1 (feed flow rate) and -20 in d_2 (feed temperature) with or without the regulation of feed-forward control. It is shown that the new proposed control scheme in conjunction with dynamic feed-forward controller presents improved disturbance rejection for this system.

As seen in Fig. 7, the transient performance of DyPLS based IMC strategy is quite similar to the work presented by Kaspar and Ray. It is shown that the results of ORC method are better than other control strategies based on data model, because ORC method had used very detailed information of the process including the specific structure and parameters.

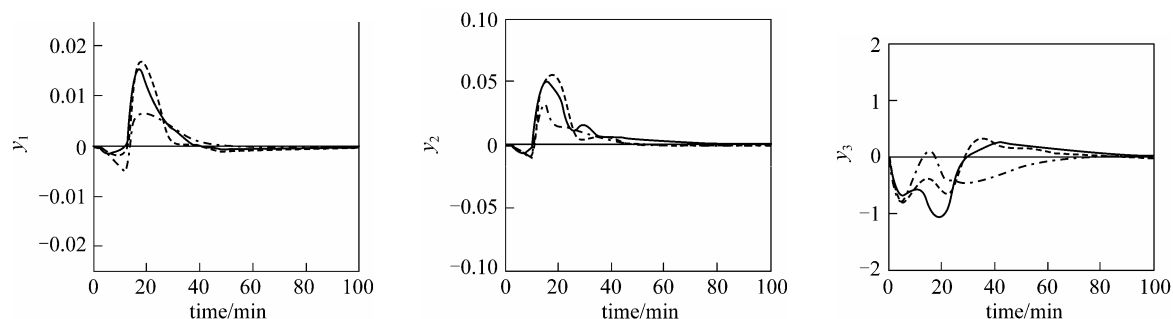


Figure 7 Column response to a change of +0.2 in d_1
— DyPLS based IMC; ---- ORC strategy; Kaspar/Ray method

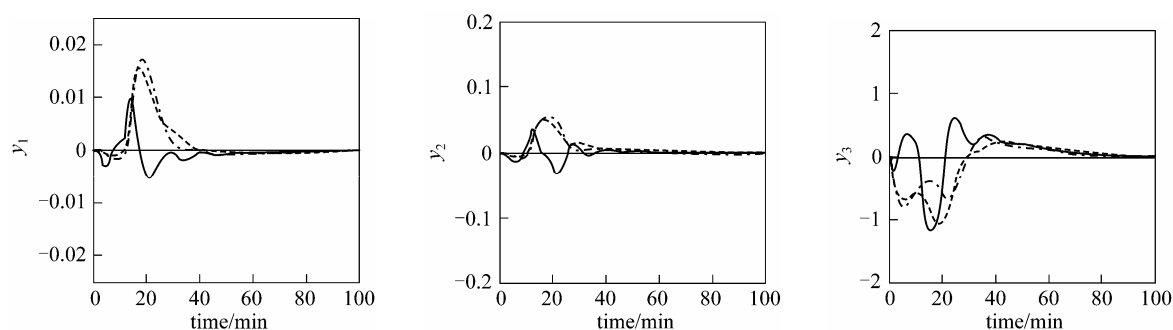


Figure 8 Comparison of column response to a change of +0.2 in d_1 with and without feed-forward controller
— dynamic feed-forward controller; ---- without feed-forward controller; Kaspar/Ray method

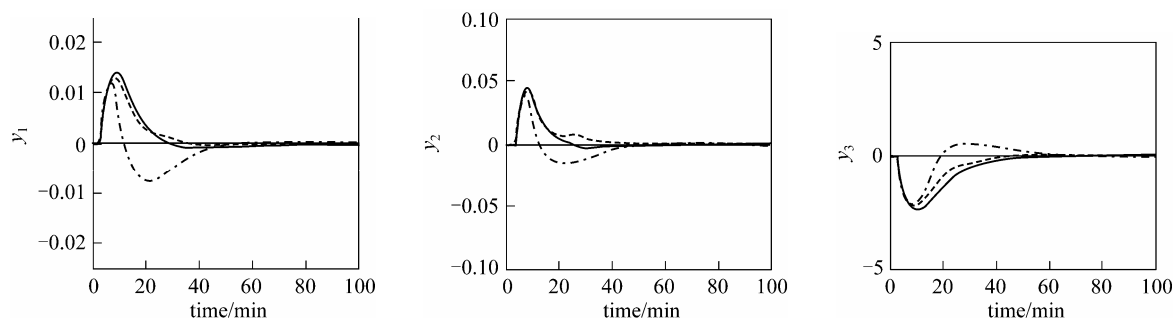


Figure 9 Column response to a change of -20 in d_2
— DyPLS based IMC; ---- ORC strategy; Kaspar/Ray method

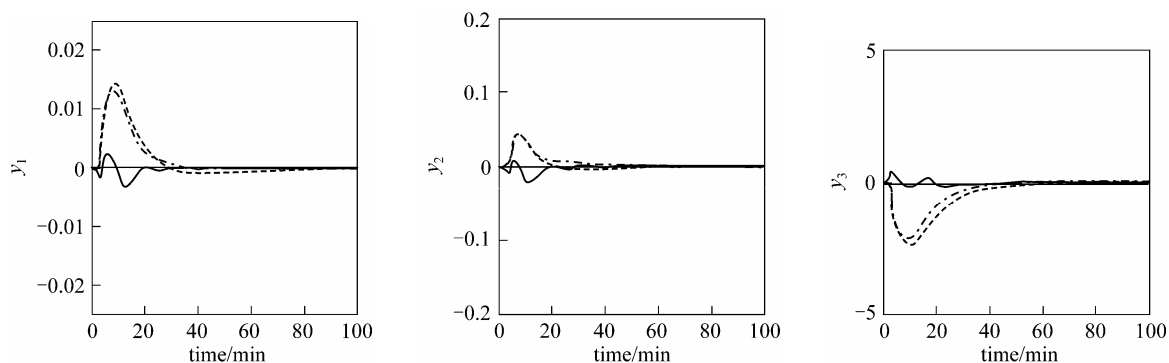


Figure 10 Comparison of column response to a change of -20 in d_2 with and without the feed-forward control
 — dynamic feed-forward control; without feed-forward control; ---- Kaspar/Ray method

Table 2 Performance index comparison in response to disturbances in ORC system

	IMC			IMC + dynamic FF			ORC		
	y_1	y_2	y_3	y_1	y_2	y_3	y_1	y_2	y_3
IAE of D1	0.1955	0.8241	26.025	0.1165	0.4707	22.016	0.1569	0.4577	20.2109
ISE of D1	0.0018	0.0228	15.255	0.0005	0.0078	11.774	0.0007	0.0072	8.5037
IAE of D2	0.2031	0.4753	46.6581	0.0316	0.2043	5.3861	0.2259	0.5261	35.030
ISE of D2	0.0017	0.0121	72.049	0.0001	0.0023	0.6427	0.0015	0.0093	42.487

Note: D1 and D2 are two types of disturbances (D1: +0.2 in d_1 ; D2: -20 in d_2).

However, it is found from Fig. 8 that the performance is slightly improved by incorporating the dynamic feed-forward controller. For the measurable disturbance d_1 , the integral of the absolute value of the error (IAE) and integral of square of the error (ISE) values for ORC method and IMC plus dynamic feed-forward strategy are very close as shown in Table 2.

As for the second disturbance, the responses in Fig. 9 show little different between the DyPLS based IMC and Kaspar/Ray method. However, with the same feed-forward controller as the previous case, an obvious improvement in rejecting d_2 is achieved as shown in Fig. 10. The feed-forward control provides better performance than ORC method and Kaspar/Ray method, especially for the transient behavior of y_3 , which is the most difficult output to be regulated in the previous cases and is barely fluctuated through the overall response under the dynamic feed-forward control. The advantage of using the method proposed here is also testified by performance index as shown in Table 2.

5 CONCLUSIONS

In this paper, an internal model control (IMC) scheme based on a dynamic partial least squares (DyPLS) framework for multi-input multi-output systems with time delay has been proposed. The filter structure is optimized via applying off-line least squares method in each subspace so that the model mismatch is minimized. A new PLS-based feed-forward control scheme is developed in conjunction with feedback control tunnel as well. The simulation results for a 3×3

distillation column further demonstrate the ability of the new strategy to outperform conventional methods. In view of the flexibility that internal model control provides in dealing with the processes with time delay, the proposed PLS-based IMC is potentially applicable to a wide class of process control problems.

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