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Multi-loop adaptive internal model control based on a dynamic partial least squares model*

Zhao ZHAO, Bin HU, Jun LIANG[†‡]

(*State Key Lab of Industrial Control Technology, Department of Control Science & Engineering, Zhejiang University, Hangzhou 310027, China*)

[†]E-mail: jliang@iipc.zju.edu.cn

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Abstract: A multi-loop adaptive internal model control (IMC) strategy based on a dynamic partial least squares (PLS) framework is proposed to account for plant model errors caused by slow aging, drift in operational conditions, or environmental changes. Since PLS decomposition structure enables multi-loop controller design within latent spaces, a multivariable adaptive control scheme can be converted easily into several independent univariable control loops in the PLS space. In each latent subspace, once the model error exceeds a specific threshold, online adaptation rules are implemented separately to correct the plant model mismatch via a recursive least squares (RLS) algorithm. Because the IMC extracts the inverse of the minimum part of the internal model as its structure, the IMC controller is self-tuned by explicitly updating the parameters, which are parts of the internal model. Both parameter convergence and system stability are briefly analyzed, and proved to be effective. Finally, the proposed control scheme is tested and evaluated using a widely-used benchmark of a multi-input multi-output (MIMO) system with pure delay.

Key words: Partial least squares (PLS), Adaptive internal model control (IMC), Recursive least squares (RLS)
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1 Introduction

In a chemical process, a plant's operating system may be unknown, or may change with time due to aging, drift in operational conditions, or environmental changes (Sastry, 1994). Under such circumstances, traditional control strategies fail to achieve good performance or even to stabilize the system. One has to resort to system identification techniques to firstly obtain an appropriate model for the plant, and then attempt to update the parameters online to account for the plant changes. In the past fifty years, adaptive control as an alternative strategy to deal with varying plant conditions, has been formulated and greatly developed in different structures (Astrom and Wittenmark, 1973; Astrom *et al*., 1977; Su and Wang, 2006). The increasingly popular method of parameter online updating has been applied to a variety of control schemes, including model predictive control, internal model control (IMC), and neural network control (Datta and Xing, 1998; Qi and Yao, 2004; Su and Wang, 2006), and has helped to advance research towards coping with more complex and practical systems.

IMC is a very popular strategy in process control, and attracts a lot of attention because of its simple and explicit model structure. It is noted that the IMC structure is inherent in most model predictive control schemes, such as model algorithm control and dynamic matrix control (DMC), which have been extensively applied in process systems (Garcia and Morari, 1982). Therefore, many studies on expanding IMC structure and exploring its potential to handle problems in nonlinear control, decoupling control, and adaptive control, have been presented (Goodwin

‡ Corresponding author

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et al., 1980; Xie and Rad, 2000). Datta and Ochoa (1996) first proposed a complete theoretical design and analysis for adaptive IMC, involving online adaptation of the plant model, and the stability and asymptotic performance of the whole system. By minimizing the H_2 and H_∞ performance indices, a point-wise adaptive optimal controller and a robust adaptive H_∞ optimal controller based on the IMC structure were further developed, which are able to update the IMC parameters online using a series-parallel identification model (Datta and Ochoa, 1998; Datta and Xing, 1999). However, these developments are applicable only to single-input single-output (SISO) systems. There are no theoretical guarantees that the feasibility and applicability of adaptive IMC in SISO case can readily extend to multi-input multi-output (MIMO) case since MIMO systems are more complex. In this paper, we will attempt to extend the adaptive IMC scheme to the MIMO case using a different adaptation algorithm.

The partial least squares (PLS) technique (Geladi and Kowalski, 1986) is a well-known decomposition method that takes into consideration both collinear relations among unidirectional variables and correlations between bidirectional variables. Through building a couple of latent variables orthogonal to each other, the original multivariable system can be decomposed into several subspaces, which can represent the whole system in a large scale. Considering the advantages of automatic decoupling and pairing in a PLS model, Kaspar and Ray (1992; 1993) creatively extended the traditional PLS structure to a dynamic mode by introducing a dynamic filter within the latent spaces, and proposed a new control framework based on a dynamic PLS (DyPLS) model. To account for nonlinearities in the plant, many researchers have incorporated nonlinear transformations into the latent spaces, such as polynomial, neural networks, and the Takagi-Sugeno structure (Wold *et al*., 1989; Qin and Mcavoy, 1992; Wold, 1992; Bang *et al*., 2002; Doymaz *et al*., 2003; Abdel-Rahman and Lim, 2009). Aside from extensive applications in modeling and fault diagnosis, different transformed PLS models have been used to construct comprehensive control schemes that effectively convert MIMO control problems into several multi-loop univariable controller designs. Combining the advantage of a PLS decoupling structure and the superior control performance that IMC presents for a chemical plant with significant dead time, Hu *et al*. (2010) designed a multi-loop IMC strategy with a DyPLS structure to handle multivariable systems with pure delay. With respect to applying an adaptive scheme in a PLS model, Chen and Cheng (2004) and Chen *et al*. (2005) demonstrated how to design multi-loop adaptive proportional-integral-derivative controllers using a PLS structure. However, the adaptive rule proposed was intended to be used to deal with plant nonlinearities instead of considering plant model changes. The aim of this paper is to consider seriously plant model changes, and to propose a multi-loop adaptive IMC strategy to achieve satisfactory performance.

2 Partial least squares (PLS) modeling

2.1 Overview of the partial least squares (PLS) model

A traditional PLS model is commonly described as consisting of an inner model that deals with regression between latent variables, and an outer model that extracts the principal components (Wold *et al*., 2001).

Suppose $\boldsymbol{X}=(x_{ij})_{l\times r}$ represents the input dataset and $\boldsymbol{Y}=(y_{ij})_{l\times v}$ represents the output dataset, where l, r, and v denote the numbers of observations, independent variables, and dependent variables respectively. The outer model can be expressed by iteratively extracting principal components:

$$\boldsymbol{X}-\boldsymbol{E}^*=\sum_{a=1}^{A}\boldsymbol{t}_a\boldsymbol{p}_a^{\mathrm{T}}=\boldsymbol{T}\boldsymbol{P}^{\mathrm{T}}, \quad (1)$$

$$\boldsymbol{Y}-\boldsymbol{F}^*=\sum_{a=1}^{A}\boldsymbol{u}_a\boldsymbol{q}_a^{\mathrm{T}}=\boldsymbol{U}\boldsymbol{Q}^{\mathrm{T}}, \quad (2)$$

where A denotes the number of latent variables, which is practically determined based on the percentage of variance or by a statistical method such as cross validation. $\boldsymbol{p}_a$ and $\boldsymbol{q}_a$ are the ath loading vectors of the loading matrices $\boldsymbol{P}$ and $\boldsymbol{Q}$, while $\boldsymbol{t}_a$ and $\boldsymbol{u}_a$ are the ath orthogonal vectors of the score matrices $\boldsymbol{T}$ and $\boldsymbol{U}$, and $\boldsymbol{T}$ and $\boldsymbol{U}$ are the projections from the original space. $\boldsymbol{E}^*$ and $\boldsymbol{F}^*$ are residual matrices of $\boldsymbol{X}$ and $\boldsymbol{Y}$, respectively.

The formulations below show the PLS inner model, which reveals the algebraic relationship between the input and output latent variables:

$$\boldsymbol{u}_a = b_a \boldsymbol{t}_a, \tag{3}$$

$$b_a = \boldsymbol{u}_a^{\mathrm{T}} \boldsymbol{t}_a / \boldsymbol{t}_a^{\mathrm{T}} \boldsymbol{t}_a, \tag{4}$$

$$\boldsymbol{Y} - \boldsymbol{F}^* = \sum_{a=1}^{A} b_a \boldsymbol{t}_a \boldsymbol{q}_a^{\mathrm{T}} = \boldsymbol{TBQ}^{\mathrm{T}}, \tag{5}$$

where $\boldsymbol{B}$ is a diagonal matrix containing the regression coefficients b_a of the score model. However, the standard PLS model is not able to interpret correctly the dynamic process because of its pure linear algebraic structure. Therefore, it is necessary to introduce a dynamic structure to gain a better representation of the model.

2.2 Dynamic PLS modeling

In recent years, several kinds of DyPLS structures have been proposed as extensions of the traditional PLS modeling approach, attempting to include time-series structure in PLS frameworks so that the dynamic characteristic of plants can be included. In the method proposed by Kaspar and Ray (1992; 1993), the input data is first filtered, and the standard PLS model is used to represent the relations between the output data and the transformed input data. Another method is to incorporate autoregressive exogenous (ARX) structure into the PLS inner model, forming a dynamic extension of the PLS model. The general mathematic expression of the DyPLS inner modeling is given as

$$\boldsymbol{u}_a = \boldsymbol{H}_a(\boldsymbol{t}_a), \tag{6}$$

where $\boldsymbol{H}_a(\boldsymbol{t}_a)$ denotes the general formation for an ARX model.

By combining Eqs. (5) and (6), the final DyPLS form can be written as

$$\boldsymbol{Y} - \boldsymbol{F} = \sum_{a=1}^{A} \boldsymbol{H}_a(\boldsymbol{t}_a) \boldsymbol{q}_a^{\mathrm{T}} = \boldsymbol{H}(\boldsymbol{T}) \boldsymbol{Q}^{\mathrm{T}}, \tag{7}$$

$$\boldsymbol{H}(\boldsymbol{T})\boldsymbol{Q}^{\mathrm{T}} = \begin{pmatrix} \boldsymbol{H}_1(\boldsymbol{t}_1) & \cdots & 0 \\ \vdots & & \vdots \\ 0 & \cdots & \boldsymbol{H}_A(\boldsymbol{t}_A) \end{pmatrix} \begin{pmatrix} \boldsymbol{q}_1^{\mathrm{T}} \\ \vdots \\ \boldsymbol{q}_A^{\mathrm{T}} \end{pmatrix}, \tag{8}$$

where $\boldsymbol{F}$ is the residual matrix of $\boldsymbol{Y}$ using the DyPLS model.

As shown above, using the DyPLS modeling, the MIMO process can be decomposed into several SISO subsystems in the latent space. Hence, the problem of multi-variable model identification and parameter updating can be treated as several independent single-variable model identification problems. Note that the validity of an empirical model always depends on the effectiveness of modeling data to truly mimic the dynamic and steady state performance. It is of great importance to take modeling errors, or slowly varying plant parameters into consideration, because either of these factors could contribute to an unstable control system giving rise to a catastrophe in the process.

Hence, in the next section, an adaptive IMC strategy based on a DyPLS model is proposed to handle the uncertainty in the structure or parameters of the plant. We will focus on parameter identification and how to apply a recursive least squares (RLS) method to yield an iterative algorithm for online parameter updating.

2.3 Online parameter updating of a Dynamic PLS model based on recursive least squares (RLS)

In the previous section, we have established a dynamic inner model by adding an ARX structure into the latent variable space. Considering the mismatch between the model and the plant as well as the uncertainty of the structure or parameters, it is necessary to introduce an effective method to adjust the DyPLS model online to adapt to these changes such that the error between the model and the plant is able to be minimized. Here we introduce the RLS method to update the model parameters online.

As the pivotal factor in the DyPLS model, the ARX structure has a direct impact on the similarity between the model and the plant, which can be formulated in terms of a time series scheme. The projection of the practical plant output in the ath latent subspace is given as

$$u_a(t) = \boldsymbol{\varphi}_a(t) \boldsymbol{\theta}_a^*(t), \tag{9}$$

where $\boldsymbol{\theta}_a^*(t)$ is considered as the real value of parameter $\boldsymbol{\varphi}_a(t)$, which contains the current and past information of the input and output, denoting the regression factor at time t, and is expressed as follows:

$$\begin{aligned} \boldsymbol{\theta}_a^*(t) = [&-a_{a1}^*(t), -a_{a2}^*(t), \ldots, -a_{an}^*(t), \\ &b_{a0}^*(t), b_{a1}^*(t), \ldots, b_{am}^*(t)]^{\mathrm{T}}, \end{aligned} \tag{10}$$

$$\boldsymbol{\varphi}_a(t)=[u_a(t-1),u_a(t-2),...,u_a(t-n),\\ t_a(t-d_a),t_a(t-d_a-2),...,t_a(t-d_a-m)], \tag{11}$$

where n and m are orders of the output and input data, respectively; $a_{ai}^*(t)$ and $b_{aj}^*(t)$ (i=1, …, n; j=0, …, m) are considered as the real ARX model parameters; and d_a represents the delay time in latent subspace.

Similarly, the inner model of the DyPLS model can be written as

$$u_a^{\text{PLS}}(t)=\boldsymbol{\varphi}_a(t)\boldsymbol{\theta}_a(t), \tag{12}$$

$$\boldsymbol{\theta}_a(t)=[-a_{a1}(t),-a_{a2}(t),...,-a_{an}(t),\\ b_{a0}(t),b_{a1}(t),...,b_{am}(t)]^{\text{T}}, \tag{13}$$

where $\boldsymbol{\theta}_a(t)$ is the estimated value of the parameter vector. Suppose that the resulting system will stabilize after a finite period of time, our goal is to make the DyPLS output as close as possible to the plant within a fixed timeframe. The optimal objective in the real space can be represented as

$$\min J=\frac{1}{2}\sum_{t=1}^{n}(\boldsymbol{y}(t)-\boldsymbol{y}^{\text{PLS}}(t))^2,$$

where $\boldsymbol{y}(t)$ and $\boldsymbol{y}^{\text{PLS}}(t)$ represent the process and the PLS model output vectors at time t, respectively. The optimal objective can be converted to

$$\min J=\frac{1}{2}\sum_{t=1}^{n}(\boldsymbol{u}(t)-\boldsymbol{u}^{\text{PLS}}(t))^2,\\ \boldsymbol{u}(t)=[u_1(t),u_2(t),...,u_A(t)]^{\text{T}},\\ \boldsymbol{u}^{\text{PLS}}(t)=\left[u_1^{\text{PLS}}(t),u_2^{\text{PLS}}(t),...,u_A^{\text{PLS}}(t)\right]^{\text{T}},$$

where $\boldsymbol{u}(t)$ and $\boldsymbol{u}^{\text{PLS}}(t)$ represent the process and PLS model output vectors at time t in the latent spaces. Then we can get

$$\begin{aligned}\min J&=\frac{1}{2}\sum_{t=1}^{n}(\boldsymbol{u}(t)-\boldsymbol{u}^{\text{PLS}}(t))^2\\ &=\frac{1}{2}\sum_{t=1}^{n}\sum_{a=1}^{A}(u_a(t)-u_a^{\text{PLS}}(t))^2\\ &=\frac{1}{2}\sum_{a=1}^{A}\sum_{t=1}^{n}(u_a(t)-u_a^{\text{PLS}}(t))^2\\ &=\min\tilde{J}_1+\min\tilde{J}_2+\ldots+\min\tilde{J}_a+\ldots+\min\tilde{J}_A,\end{aligned} \tag{14}$$

where $\tilde{J}_a=\frac{1}{2}(\boldsymbol{u}_a(t)-\boldsymbol{u}_a^{\text{PLS}}(t))^2$.

The overall optimal equation can then be applied to minimize the model error in the latent subspace:

$$\begin{aligned}\min\tilde{J}_a&=\frac{1}{2}\sum_{t=1}^{n}(u_a(t)-u_a^{\text{PLS}}(t))^2\\ &=\frac{1}{2}\sum_{t=1}^{n}(\boldsymbol{\varphi}_a(t)\boldsymbol{\theta}_a^*(t)-\boldsymbol{\varphi}_a(t)\boldsymbol{\theta}_a(t))^2\\ &=\frac{1}{2}\sum_{t=1}^{n}\boldsymbol{\varphi}_a(t)^2(\boldsymbol{\theta}_a^*(t)-\boldsymbol{\theta}_a(t))^2.\end{aligned} \tag{15}$$

By applying the RLS method, we can obtain the time varying recursive expression of $\boldsymbol{\theta}_a(t)$, as well as the intermediate parameter $\boldsymbol{P}(t)$:

$$\hat{\boldsymbol{\theta}}_a(t)=\hat{\boldsymbol{\theta}}_a(t-1)+\frac{\boldsymbol{P}(t-1)\boldsymbol{\varphi}_a^{\text{T}}(t)}{\lambda+\boldsymbol{\varphi}_a(t)\boldsymbol{P}(t-1)\boldsymbol{\varphi}_a^{\text{T}}(t)}\\ \left(u_a(t)-\boldsymbol{\varphi}_a(t)\hat{\boldsymbol{\theta}}_a(t-1)\right), \tag{16}$$

$$\boldsymbol{P}(t)=\frac{1}{\lambda}\left(\boldsymbol{I}-\frac{\boldsymbol{P}(t-1)\boldsymbol{\varphi}_a^{\text{T}}(t)\boldsymbol{\varphi}_a(t)}{\lambda+\boldsymbol{\varphi}_a(t)\boldsymbol{P}(t-1)\boldsymbol{\varphi}_a^{\text{T}}(t)}\right)\boldsymbol{P}(t-1), \tag{17}$$

where $\boldsymbol{P}(t)\in\mathbf{R}^{(n+m+1)\times(n+m+1)}$ is used to ensure that the initial iterative value is in a reasonable range, and where the initial value $P(0)$ is chosen as a diagonal matrix $\sigma\boldsymbol{I}$, where σ=50–1000, and $\boldsymbol{I}$ is a unit matrix. The above recursive expression also introduces a scalar constant λ to keep the denominator from zero so that convergence of the final parameters is ensured.

3 Adaptive dynamic PLS (DyPLS) based internal model control (IMC) design

3.1 IMC based on the RLS-DyPLS model

As a model-based control strategy, IMC directly incorporates the minimum phase information of the internal model as part of its structure, and uses it to achieve perfect control performance while no model-plant mismatch exists. In this section, a self-tuning IMC scheme based on the RLS-DyPLS model is proposed to yield a closed-loop control system, which is very simple but effective in dealing with plant changes. There are two principal advantages, which make IMC the ideal controller. One is that no extra adaptive laws are needed to adjust the controller; i.e., the IMC controller automatically follows the update of the model parameters. With the inverse of the DyPLS model's static gain, the other advantage is that it will largely achieve error-free system output, since the online updating algorithm can minimize the deviation between the actual process and the model (Eq. (15)).

Considering the open-loop system is stable, β_i (i=1, 2, …, h_a) are the zero points outside the unit circle of the discrete transfer function $H_a(q^{-1})$, where q^{-1} is a backward shift operator, and $\overline{\beta}_i$ is the complex conjugate of β_i. The Blashcke product of the DyPLS' non-minimum phase part can be denoted as

$$H_{an}(q^{-1})=q^{-d_a}\prod_{i=1}^{h_a}\frac{(1-(\overline{\beta}_i)^{-1})(1-\beta_i q^{-1})}{(1-(\overline{\beta}_i)^{-1}q^{-1})(1-\beta_i)}, \quad (18)$$

and the minimum phase part is

$$\begin{aligned} H_{\mathrm{am}}(q^{-1}) &= \tilde{A}_a(q^{-1})/\tilde{B}_a(q^{-1}),\\ \tilde{A}_a(q^{-1}) &= 1+\tilde{a}_{a1}q^{-1}+\cdots+\tilde{a}_{an}q^{-n},\\ \tilde{B}_a(q^{-1}) &= 1+\tilde{b}_{b1}q^{-1}+\cdots+\tilde{b}_{bm}q^{-m}. \end{aligned} \quad (19)$$

$H_a(q^{-1})$ can be decomposed to the product of the minimum phase part and the non-minimum phase part:

$$H_a(q^{-1})=H_{an}(q^{-1})H_{\mathrm{am}}(q^{-1}). \quad (20)$$

Note that the IMC actually chooses the minimum phase part as part of the controller, in which the parameter set $\{\tilde{a}_{ai}\}$ (i=1, 2, ···, n) of the numerator polynomial $\tilde{A}_a(q^{-1})$ and the parameter set $\{\tilde{b}_{ai}\}$ (i=1, 2, ···, m) of the denominator polynomial $\tilde{B}_a(q^{-1})$ can be regarded as a subset of the original model's minimum phase part. A classic IMC control strategy generally includes three parts: the inverse of the model's minimum phase part, the low pass filter, and the internal model. The relation between the three parts is clearly demonstrated in Fig. 1, where $e_a(t)$ serves as the feedback error signal as well as the input of the IMC, and $t_a(t)$ is the output of the controller, which can be expressed as follows:

$$e_a(t)=u_a^{\mathrm{set}}(t)-u_a(t)+u_a^{\mathrm{PLS}}(t), \quad (21)$$

$$t_a(t)=F_a(q^{-1})H_{\mathrm{am}}^{-1}(q^{-1})e_a(t), \quad (22)$$

where $u_a^{\mathrm{set}}(t)$ is the ath set point value at time t, and the structure of the low pass filter can be selected as

$$F_a(q^{-1})=\left(\frac{1-\lambda_a}{1-\lambda_a q^{-1}}\right)^{N_a}, \quad (23)$$

where the positive integer N_a is chosen so that $F_a(q^{-1})H_{\mathrm{am}}^{-1}(q^{-1})$ is semi-proper or proper, and the choice of the low filter parameter λ_a will determine the balance between the robustness and sensitivity on the whole system. Note that $\boldsymbol{G}_{pa}$ represents the transfer function of the compensated plant ($\boldsymbol{PW}_x\boldsymbol{G}_p\boldsymbol{W}_y^{-1}\boldsymbol{Q}^{+}$) in the ath loop, where $\boldsymbol{G}_p$ is the transfer function of the controlled plant, $\boldsymbol{P}$ and $\boldsymbol{Q}$ are the loading matrices, $\boldsymbol{W}_x$ and $\boldsymbol{W}_y$ are the diagonal scaling matrices, and $\boldsymbol{Q}^{+}$ is an appropriate inverse of $\boldsymbol{Q}$.

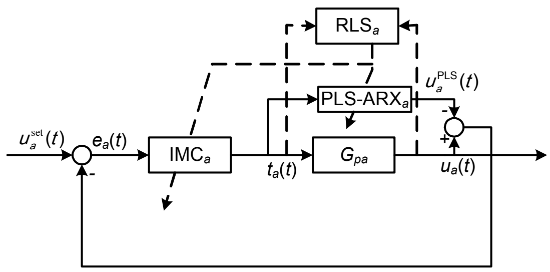

Fig. 1 IMC based on the DyPLS subspace

Because of the self-decoupling character in the PLS method, we can design an independent adaptive IMC controller in each latent variable subspace. Generally, the multi-variable controller system can be simplified to several single variable controller design problems (Fig. 2). The control block, DyPLS latent variable IMC (DyPLS-LVIMC), can be a combination of several LVIMCs. Unlike the conventional IMC multi-loop design that is highly dependent on the structure of the practical process, the technique investigated here decomposes the MIMO control system into a couple of SISO loops, to which the traditional IMC strategy can be easily applied without rigorous structures in latent variable space.

The procedure can be summarized as follows.

Phase I. Identify the DyPLS model and compute the IMC parameters.

Step 1: Train the DyPLS model using observational data. There will be several SISO loops in the latent space.

Step 2: Based on the DyPLS model, calculate the parameters of the latent variable IMC.

Phase II. Update the parameters of the LVIMC and the process input online.

Step 3: At new sample time t, obtain the process input data and output data. If the parameters do not need to be changed, go to step 5. Otherwise, go to step 4, and update the DyPLS model and the parameters of LVIMC.

Step 4: Based on the current input and output data, calculate the new varying parameter $\hat{\boldsymbol{\theta}}_a(t)$ of each ARX structure in the latent space using Eqs. (16) and (17). Then update the parameters of the LVIMC using the traditional IMC strategy.

Step 5: With the new sample data and DyPLS-LVIMC controller, the new process input can be calculated. At the next sampling time k (k=k+1), collect the process input and output data, and repeat Phase II procedure.

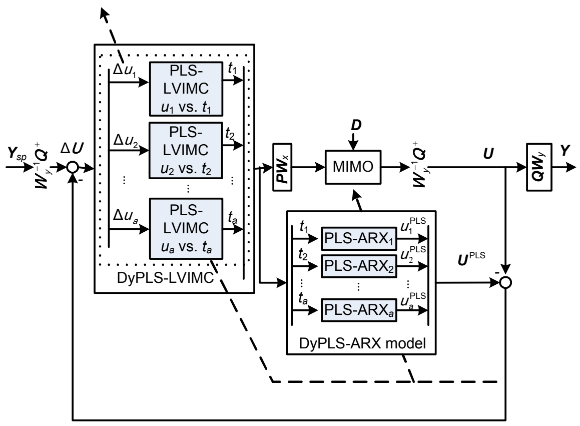

Fig. 2 Multi-loop adaptive IMC based on the dynamic PLS
$\boldsymbol{Y}_{sp}$: set point vector; $\boldsymbol{D}$: disturbance part; $\boldsymbol{U}^{\rm PLS}$: DyPLS-ARX model output; and $\Delta\boldsymbol{U}=\boldsymbol{Y}_{sp}W_y^{-1}\boldsymbol{Q}^{+}-\boldsymbol{U}+\boldsymbol{U}^{\rm PLS}$

3.2 Parameter convergence and stability analysis

Two problems need to be considered before applying the above algorithm. The first involves the discussion of global convergence, which guarantees that the parameters do not diverge to infinite as the adaptive rule proceeds. The study of this property is of great interest and an essential prerequisite to the analysis of the stability of the whole system. The second problem is the investigation of the stability of proposed adaptive IMC system based on the DyPLS framework. As we will see, the validity of the previous argument leads to a stable adaptive control system. We will discuss the two problems separately below.

3.2.1 Parameter convergence

In this study, a DyPLS modeling technique is used to decompose a complex MIMO plant into several univariable subsystems so that a widely-used RLS algorithm is available for treating it as a SISO case. The RLS rule implementation for a multivariable deterministic system is far more difficult than that for a univariable case, because the algorithm may suffer from an unsuitable structure or exponentially rising computation time with increased dimensions.

Global convergence analysis for RLS algorithms was established by Goodwin *et al.* (1980). The results will be briefly reviewed here to facilitate discussion of the stability problem.

The analysis of the model convergence within the DyPLS latent spaces is based on a discrete Lyapunov function. Considering the point-wise error $\tilde{\boldsymbol{\theta}}_a(t)$ between the estimator $\hat{\boldsymbol{\theta}}_a(t)$ and the actual value $\boldsymbol{\theta}_a$, the Lyapunov function is given as

$$\boldsymbol{V}(t)=\tilde{\boldsymbol{\theta}}_a(t)^{\rm T}\boldsymbol{P}(t-1)^{-1}\tilde{\boldsymbol{\theta}}_a(t), \tag{24}$$

$$\tilde{\boldsymbol{\theta}}_a(t)=\hat{\boldsymbol{\theta}}_a(t)-\boldsymbol{\theta}_a. \tag{25}$$

In the sense that $\boldsymbol{V}(t)$ is a bounded, non-negative, non-increasing function,

$$\lim_{t\to\infty}\frac{\tilde{\boldsymbol{\theta}}_a(t)^{\rm T}\boldsymbol{\varphi}_a(t)^{\rm T}\boldsymbol{\varphi}_a(t)\tilde{\boldsymbol{\theta}}_a(t)}{1+\boldsymbol{\varphi}_a(t)\boldsymbol{P}(t-1)\boldsymbol{\varphi}_a(t)^{\rm T}}=0. \tag{26}$$

Hence,

$$\lim_{t\to\infty}\frac{e_a(t)}{[1+\boldsymbol{\varphi}_a(t)\boldsymbol{P}(t-1)\boldsymbol{\varphi}_a(t)^{\rm T}]^{1/2}}=0, \tag{27}$$

where

$$\begin{aligned}e_a(t)&=u(t)-u_a^{\rm PLS}(t)=-\boldsymbol{\varphi}_a(t)\tilde{\boldsymbol{\theta}}_a(t)\\&=-\boldsymbol{\varphi}_a(t)(\hat{\boldsymbol{\theta}}_a(t)-\boldsymbol{\theta}_a).\end{aligned}$$

The proof is omitted here. For more details, please refer to Goodwin *et al.* (1980).

We can derive two conclusions from the above results: (1) With all system zeros contained in the unit circle, the estimator $\hat{\boldsymbol{\theta}}_a(t)$ will approach a certain value gradually, ensuring the stability of the update algorithm. (2) The error $e_a(t)$ well represents the model mismatch in the time domain (Fig. 1), fulfilling the objective of the RLS algorithm to minimize the mismatch. Our goal is to reduce the model mismatch effect on the control system as much as possible so that the IMC structure can achieve perfect performance at the end. However, note that a stable updating rule cannot guarantee the stability of the whole system because whether all signals in the system channel are necessarily bounded is unknown. Therefore, this question gives rise to another important discussion pertaining to the boundedness of the signals.

3.2.2 Stability analysis

The system stability is always of primary interest, and has a direct impact on the perfect performance under the proposed control algorithm. If the updated DyPLS model is an exact image of the plant, the global stability of the system rests on the stable controller and plant structures. In practice, such a condition is well satisfied. In Section 2.3, we noted that our goal is to minimize the mismatch as much as possible. Hence, once optimal solutions are obtained, bounded signals within the system can be easily derived given a well matched model. For the assumption that the identified model should have all zeros strictly inside the closed unit disk, a slightly conservative selection for the delay time d_a is made in the DyPLS model.

4 Examples

To demonstrate the features of the DyPLS based multi-loop adaptive IMC scheme described above, we chose the Jerome-Ray distillation column to prove the superior control performance of a non-minimum phase system. In particular, the method proposed here is able to track the plant changes very well, and obtains a good set point and disturbance rejection performance.

Consider the 2×2 MIMO Jerome-Ray process with inverse response. The transfer function matrix of this process is given as

$$\boldsymbol{G}(s)=\begin{bmatrix}\dfrac{(-s+1)e^{-2s}}{s^2+1.5s+1} & \dfrac{0.5(-s+1)e^{-4s}}{(2s+1)(3s+1)}\\ \dfrac{0.33(-s+1)e^{-6s}}{(4s+1)(5s+1)} & \dfrac{(-s+1)e^{-3s}}{(4s^2+6s+1)}\end{bmatrix},$$

and the disturbance model is assumed as

$$\boldsymbol{G}_L(s)=\begin{bmatrix}e^{-s}/(25s+1)\\ e^{-s}/(25s+1)\end{bmatrix}.$$

Note that the Jerome-Ray process is a non-minimal phase system with zero point s=1 on the right half plane, which requires complex MIMO control algorithms to reduce the inverse response for better performance. This will probably restrict the control action and yield an unstable closed-loop. More importantly, many approaches aimed to solve multivariable problems rely on rigorous mathematic or first-principle models. Once the approximated model fails to interpret the actual process, the resulting control performance will seriously deteriorate. The DyPLS based adaptive IMC algorithm is able to effectively obtain zero offset for the steady state of the process, and also give comparative results for robustness analysis by various IMC filter parameters.

To build the DyPLS model, two input pseudo-random signals with magnitudes ranging from −1 to +1 were applied to excite the system, and the system responses were collected as part of the modeling data. The resulting DyPLS model parameters were derived as follows:

$$\boldsymbol{Q}^{+}\boldsymbol{W}_y=\begin{bmatrix}0.2802 & -0.2432\\ 0.1915 & 0.2277\end{bmatrix},$$

$$\boldsymbol{W}_x\boldsymbol{P}=\begin{bmatrix}1.3399 & 2.2280\\ -1.5520 & 1.8983\end{bmatrix},$$

$$\boldsymbol{H}(z)=\begin{bmatrix}h_{11}(z) & 0\\ 0 & h_{22}(z)\end{bmatrix},$$

$$h_{11}(z)=\frac{0.2898z-0.1741}{z^2-1.0766z+0.2784}z^{-3},$$

$$h_{22}(z)=\frac{0.0825z-0.0139}{z^2-1.7389z+0.8853}z^{-3},$$

$$\boldsymbol{\theta}_0=\begin{bmatrix}-1.0766 & 0.2784 & -0.1741 & 0.2898\\ -1.7389 & 0.8853 & -0.0139 & 0.0825\end{bmatrix},$$

where $\boldsymbol{H}(z)$ represents the DyPLS model; $h_{11}(z)$ and $h_{22}(z)$ are the z-transfer function of loops 1 and 2, respectively; and $\boldsymbol{\theta}_0$ is the initial ARX model parameter.

Without uncertainty in the process parameter, the above nominal value of the DyPLS model is applied to the IMC controller design. The adaptive algorithm is implemented only if perturbations occur in the process or the operation conditions are changed.

In such cases, two types of changes to the model structure are introduced to simulate the effect on process plant caused by the environment, working condition, or equipment degradation.

4.1 Steady state gain changes

Over time, equipment degradation is inevitable, and is expressed here as the changes in a system's steady state gain in the diagonal model. In this section, large changes in the magnitude of the diagonal element in the process, which are shown to influence significantly the stability of the whole system based on the nominal condition, are introduced.

When there is a large change in the process plant, the control strategy without an adaptive law cannot make the system stable, which matches the field experience. Enlarging the plant static gains is equivalent to automatically increasing the proportional element of the controller, which can easily lead to an unstable system. The system becomes unstable when we double the steady state gain of the diagonal matrix (Fig. 3). One possible way to eradicate this problem is to reduce the proportional part of controller so that the whole system approaches stability. However, this action will sacrifice control performance. Although the system response without an adaptive rule stabilizes by significantly adjusting the IMC parameters, it will not eliminate the model errors (indicated as variables e_1 and e_2) caused by the plant static condition changes (Fig. 4). The existence of the model error will affect the performance of the whole system in the long term, failing to achieve satisfactory control objectives.

The adaptive law proposed here is used to minimize the model error and simultaneously help the IMC to obtain a good tracking control result without sacrificing control performance (Fig. 5). Note that the model errors (e_1 and e_2) approach zero, guaranteeing good IMC performance and application.

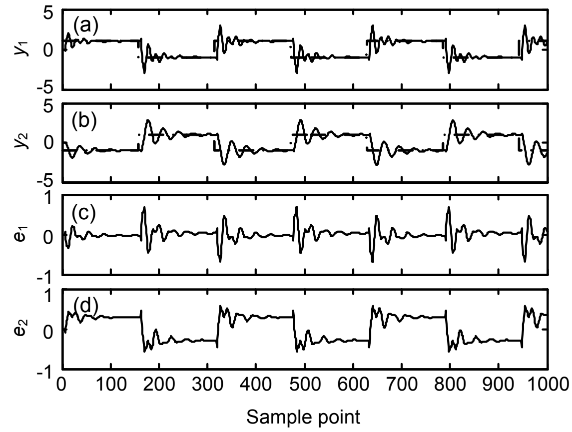

Fig. 4 Response of the system and model-plant mismatch after tuning the IMC parameters
(a) Output of the 1st process; (b) Output of the 2nd process; (c) Error of the 1st model; (d) Error of the 2nd model

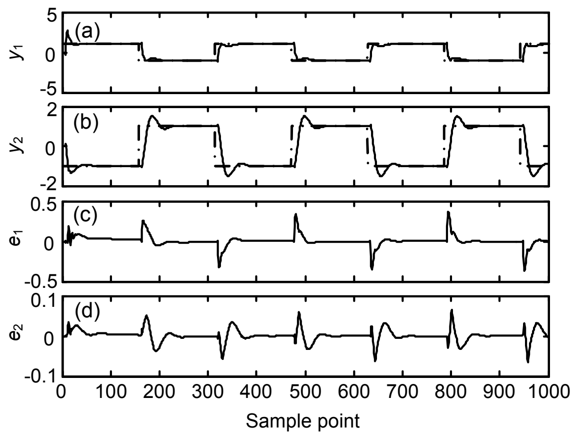

Fig. 5 Response of the system and model-plant mismatch with an adaptive law
(a) Output of the 1st process; (b) Output of the 2nd process; (c) Error of the 1st model; (d) Error of the 2nd model

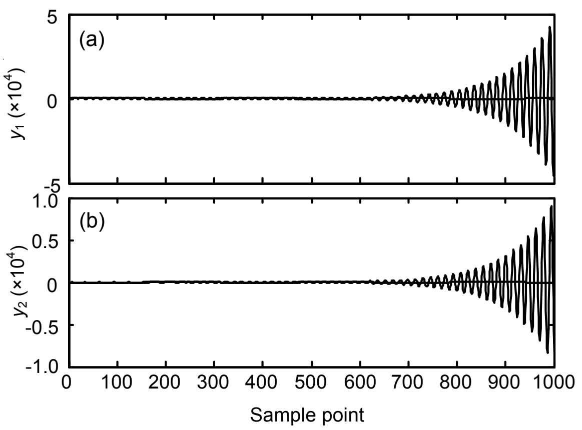

Fig. 3 Response to large steady state changes without an adaptive law
(a) Output of the 1st process; (b) Output of the 2nd process

It has been theoretically proved that the parameters will converge to certain values by applying the RLS as the adaptive algorithm. Fig. 6 shows that each parameter converges to a steady value after a short transient time. There are two sets of model parameters in the PLS space (Fig. 6).

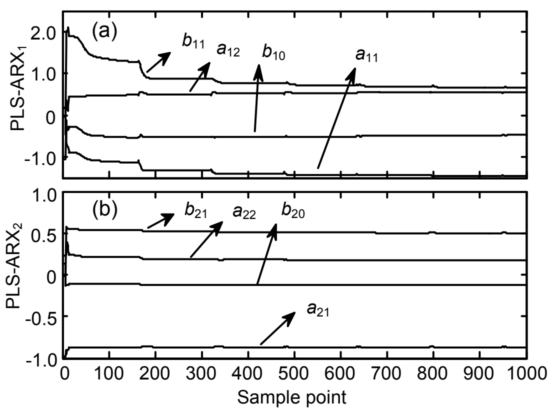

Fig. 6 Trajectory of the 1st (a) and the 2nd (b) internal model parameters in the latent variable space

a_{11}, a_{12}, b_{10}, b_{11}, a_{21}, a_{22}, b_{20}, and b_{21} are derived from Eq. (13)

4.2 Model pole changes

Another case presented here involves changes in system dynamic behavior, formulated as model pole changes in the plant. Consider the pole position changes in the transfer function of the plant, which are switched from $\frac{(-s+1)e^{-2s}}{s^2+1.5s+1}$ to $\frac{(-s+1)e^{-2s}}{s^2+4s+1}$, and from $\frac{(-s+1)e^{-3s}}{4s^2+6s+1}$ to $\frac{(-s+1)e^{-3s}}{4s^2+s+1}$. The pole position changes lead to an oscillation or even unstable behavior in the plant (Fig. 7), which creates difficulty in obtaining good performance by tuning the controller parameters as in the previous case. Although the latent output variables u_1 and u_2 can roughly track the set points after the pole changes, the model errors (e_1 and e_2) still exist and would compromise the ultimate control results in the long run (Fig. 8). By incorporating the adaptive law into the DyPLS model and the IMC structure, the final adaptive control system can not only reduce the oscillation, and speed up the response time (Fig. 9), but also eliminate the plant model errors to a larger extent (Fig. 10). In Fig. 11, the parameter sets in two latent spaces are shown to converge to certain values that validate the effectiveness of RLS in the proposed control scheme.

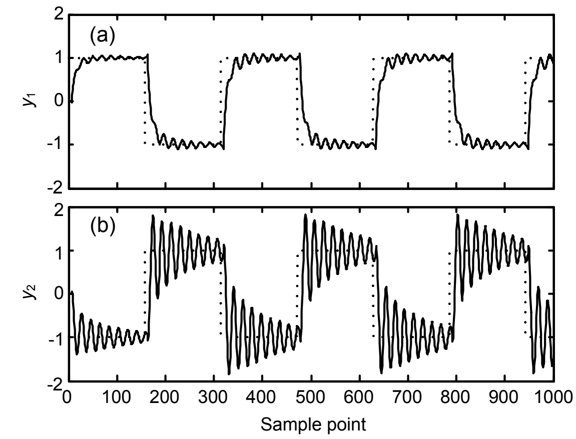

Fig. 7 Response of the system after pole changes without an adaptive law

(a) Output of the 1st process; (b) Output of the 2nd process

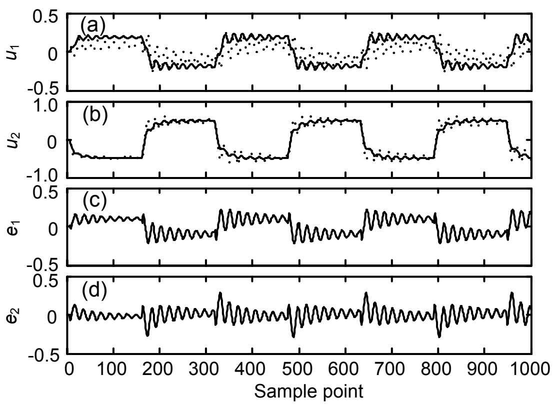

Fig. 8 Response in the latent variable space and model errors after pole changes

(a) Output of the 1st latent subspace; (b) Output of the 2nd latent subspace; (c) Error of the 1st model; (d) Error of the 2nd model

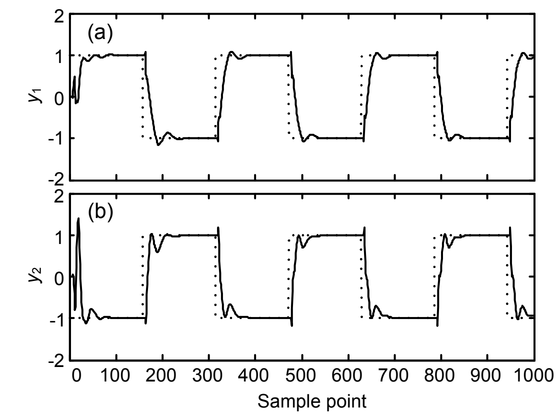

Fig. 9 Response of the system after pole changes with an adaptive law

(a) Output of the 1st process; (b) Output of the 2nd process

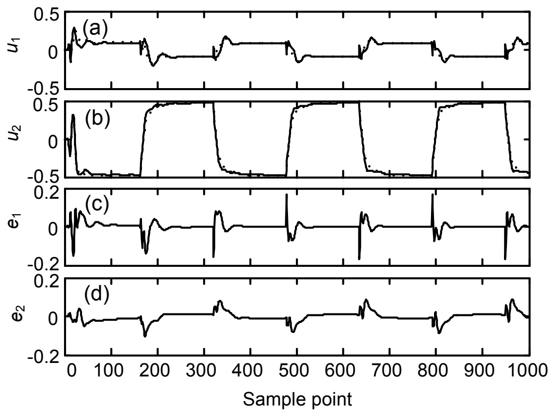

Fig. 10 Response in the latent variable space and model error after pole changes with an adaptive law

(a) Output of the 1st latent subspace; (b) Output of the 2nd latent subspace; (c) Error of the 1st model; (d) Error of the 2nd model

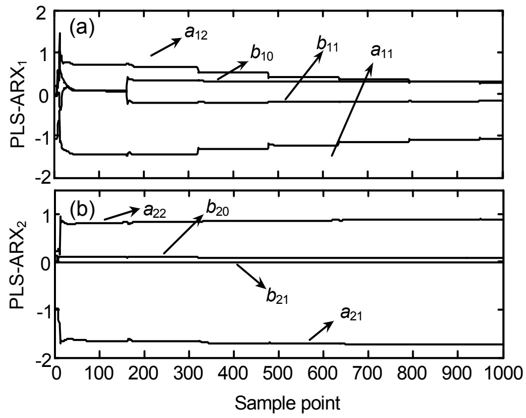

Fig. 11 Trajectory of the 1st (a) and the 2nd (b) internal model parameters after pole changes with an adaptive law

a_{11}, a_{12}, b_{10}, b_{11}, a_{21}, a_{22}, b_{20}, and b_{21} are derived from Eq. (13)

5 Conclusions

In this paper, a multi-loop adaptive IMC strategy based on a DyPLS framework is proposed to account for plant model errors caused by slow aging, drift in operational conditions, or environmental changes. The recursive least squares algorithm is applied to update the parameters of the DyPLS model online once the model error exceeds a given threshold, and effectively guarantees good control performance by reducing the model mismatch. The IMC scheme extracts the inverse of the minimum part of the internal model as its structure, which is self-tuned by explicitly updating the parameters in the internal model. The simulation of a Jerome-Ray distillation column demonstrated the effectiveness of the proposed multi-loop adaptive IMC strategy based on a DyPLS framework.

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