DESIGN OF A DATA-DRIVEN PERFORMANCE-ADAPTIVE PID CONTROLLER

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Abstract: In industrial processes, in order to improve the productivity, it is necessary to establish the performance-driven control mechanism, which the control performance is firstly evaluated, and the controller is reconstructed. Moreover, since most processes have nonlinearities, controller design schemes to deal with such systems are required. This paper describes a design scheme of data-driven performance-adaptive PID controllers. According to the proposed control scheme, the data-driven system identification which is effective for nonlinearity works corresponding to the result of modeling performance assessment, and PID parameters are computed using the newly estimated system parameters. Finally, a simulation example is discussed.

Keywords: PID control, data-base, nonlinear systems, self-adjust systems

1. INTRODUCTION

Recently, the improvement of production quality and the reduction of the production cost have been further advanced in process industries, and the control systems play an important role in such a situation. In particular, the properties of process systems have been frequently changed due to the change of operating condition and/or nonlinearity of the systems. Therefore, it is necessary to readjust the control parameters corresponding to the change of system properties in order to maintain the desired control performance. As one of such strategies, the self-tuning control has been proposed(Åström, *et al.*, 1977; Åström, 1983; Clarke and Gawthrop, 1975, 1979; Clarke *et al.*, 1987; Yamamoto and Shah, 2004). However, it is said that the recursive least squares method is not effective in nonlinear systems.

By the way, for the purpose of maintaining the safety or the productivity of industrial process, the researches on control performance assessment(CPA) have been paid to attention in last decade(Hung and Shah, 1999; Harris, 1989; Harris *et al.*, 1999; McIntosh, *et al.*, 1992; Grimble, 2002; Hung, 2003; Jelali, 2006; Qin, 1998; Agrawal and Lakshminarayanan, 2003). In process systems, it is most important problem to unify the CPA and the controller design in industries.

In this paper, a design scheme of performance-adaptive PID controllers is newly proposed. According to the proposed control scheme, the modeling performance is firstly evaluated, and system parameters are identified using the data-driven system identification which is effective in nonlinear systems, if the modeling performance is

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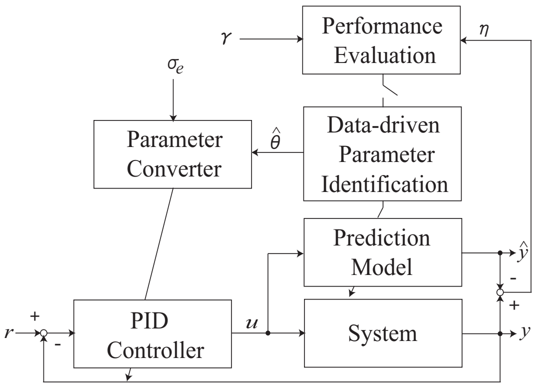

Fig. 1. Schematic figure of the proposed performance-adaptive PID control system.

not good. In addition, PID parameters are adjusted based on the estimates so that the control performance satisfies the desired performance determined in advance. Concretely, the self-tuning PID control based on generalized predictive control (GPC-PID) scheme(Katayama *et al.*, 2002) is adopted in order to tune PID parameters, and the user-specified parameter, that is, the control weighting factor which indicates the desired control performance, is chosen.

This paper is organized as follows. Firstly, the system description and the PID controller are explained, followed by the GPC-PID control scheme. Moreover, the data-driven identification scheme is described, and the tuning scheme of the control weighting factor is discussed. Also, the proposed control algorithm is summarized. Finally, the effectiveness of the proposed control scheme is numerically evaluated on a simulation example.

2. DATA-DRIVEN PERFORMANCE-ADAPTIVE PID CONTROLLER

2.1 Outline

In this paper, a PID controller design is discussed based on the following features:

(1) The model quality or performance, *i.e.* the prediction error, is monitored, and the system parameters are re-identified, if the prediction error is larger than a user-specified limit or threshold.
(2) PID parameters are adjusted using the estimates if and only if the system parameters have changed significantly.
(3) The control performance, *i.e.* variances of the control errors and the control inputs, are considered in adjusting the PID parameters, specifically the control weighting term λ in the GPC-based PID controller design scheme.

The newly proposed performance-adaptive PID control system is shown schematically in Fig.1. The proposed control system can be briefly explained as follows: The modeling quality is first evaluated as the part of model quality evaluation scheme. The system parameters are identified in the part of 'Data-driven Parameter Identification' block, if necessary. Then, the parameters included in 'Prediction Model' are updated, and the corresponding PID parameters are newly computed in the part of 'Parameter Converter' so that the desirable control performance criteria, for example on the limits on the standard deviation(σ_e), can be obtained. γ denotes the user-specified parameters corresponding to the desired modeling quality.

2.2 System description

First, the following discrete-time nonlinear system is considered:

$$y(t) = f(\phi(t-1)), \tag{1}$$

where $y(t)$ denotes the system output and $f(\cdot)$ denotes the nonlinear function. Moreover, $\phi(t-1)$ is called '*information vector*', which is defined by the following equation:

$$\begin{aligned}\phi(t-1) := [&\Delta y(t-1), \cdots, \Delta y(t-n_y),\\ &\Delta u(t-k_r-1), \cdots, \Delta u(t-k_r-1-n_u)]\,,\end{aligned} \tag{2}$$

where $u(t)$ and k_r denotes the control input and the time-delays. Also, n_y and n_u denotes the order of output and input, respectively. (2) means that the controlled object is locally described using elements included in $\phi(t-1)$.

According to the DD technique, the data is stored in the form of the information vector ϕ expressed in (3). Moreover, the query $\phi(t-1)$ is required in estimating the following system parameters:

$$\theta := [a_1, b_0, \cdots, b_{n_u}]. \tag{3}$$

That is, after some similar neighbors to the query are selected from data-base, the system parameters are estimated by employing the weighted least squares method. The system identification is discussed later in detail.

Here, it is assumed that the nonlinear system which is described as (1) is locally characterized as linear models. The local linear model is assumed to be described as the following second-order linear model:

$$A(z^{-1})y(t) = z^{-(k_m+1)}B(z^{-1})u(t) + \xi(t)/\Delta, \tag{4}$$

where k_m denotes the minimum value of the estimated time-delay, $k_m = k_r$ in case where k_m

is known. Also, z^{-1} and Δ denote the backward shift operator means $z^{-1}y(t) = y(t-1)$ and the differencing operator defined as $\Delta := 1 - z^{-1}$. If $n_y = 1$ and $n_u = 2$, $A(z^{-1})$ and $B(z^{-1})$ are polynomials given by

$$\left.\begin{array}{l} A(z^{-1}) = 1 + a_1 z^{-1} \\ B(z^{-1}) = b_0 + b_1 z^{-1} \end{array}\right\}. \tag{5}$$

That is, (4) is described by the following equation:

$$y(t) = g(\bar{\phi}(t-1)) = \bar{\phi}^T(t-1)\theta \tag{6}$$

$$\theta := [a_1, b_0, b_1]^T \tag{7}$$

$$\bar{\phi}(t-1) := [-\Delta y(t-1), \Delta u(t-k_m-1), \Delta u(t-k_m-2)]\,,^T \tag{8}$$

where $g(\cdot)$ denotes the linear function.

The controlled object can be approximately described at time t by the following 'first-order system with a time-lag element':

$$G(s) = \frac{K}{1+Ts} e^{-Ls}, \tag{9}$$

where K, T and L respectively denote the system gain, the time-constant and the time-lag, which can be obtained by calculating the following equations:

$$T = \frac{T_s}{\log(-a_1)} \tag{10}$$

$$K = \frac{b_0 + b_1}{1 + a_1} \tag{11}$$

$$L = \left(\frac{b_1}{b_0 + b_1} + k_m\right). \tag{12}$$

In the ensuing discussion, the time-lag element is approximated by a first- order pade-approximation, and the following second-order system is considered as the design-oriented model:

$$\tilde{G}(s) \simeq \frac{K(1 - \frac{L}{2}s)}{(1+Ts)(1+\frac{L}{2}s)}. \tag{13}$$

This gives us the following discrete-time model corresponding to (13):

$$\tilde{A}(z^{-1})y(t) = z^{-1}\tilde{B}(z^{-1})u(t), \tag{14}$$

where

$$\left.\begin{array}{l} \tilde{A}(z^{-1}) = 1 + \tilde{a}_1 z^{-1} + \tilde{a}_2 z^{-2} \\ \tilde{B}(z^{-1}) = \tilde{b}_0 + \tilde{b}_1 z^{-1} \end{array}\right\}. \tag{15}$$

2.3 PID controller

The following PID control law is considered:

$$\Delta u(t) = \frac{k_c \cdot T_s}{T_I} e(t) - k_c\left(\Delta + \frac{T_D}{T_s}\Delta^2\right) y(t) \tag{16}$$

$$= K_I e(t) - K_P \Delta y(t) - K_D \Delta^2 y(t), \tag{17}$$

where k_c, T_I and T_D are respectively the proportional gain, the reset-time and the derivative time. In addition, $e(t)$ is the control error signal defined by

$$e(t) := r(t) - y(t). \tag{18}$$

$r(t)$ denotes the reference signal given by the piecewise constants. Furthermore, T_s denotes the sampling interval. Here, K_P, K_I and K_D included in (17) are derived by relations $K_P = k_c$, $K_I = k_c T_s / T_I$ and $K_D = k_c T_D / T_s$.

For simplicity, (16) can be rewritten by

$$C(z^{-1})y(t) + \Delta u(t) - C(1)r(t) = 0, \tag{19}$$

where

$$C(z^{-1}) := k_c\left\{\left(1 + \frac{T_s}{T_I} + \frac{T_D}{T_s}\right) - \left(1 + \frac{2T_D}{T_s}\right)z^{-1} + \frac{T_D}{T_s}z^{-2}\right\}. \tag{20}$$

The control performance strongly depends on PID parameters(k_c, T_I, T_D). These parameters are computed using the generalized predictive PID control(GPC-PID) which has been already proposed to incorporate the idea of controller redesign as required by control performance assessment method.

2.4 Generalized Predictive Control

The GPC is one of model predictive control schemes, and since it is based on a multi-step prediction, it is an effective technique for systems with ambiguous time-delays and/or large time-delays(Clarke, *et al.*, 1987).

First, consider the following cost function of the GPC:

$$J = E\left[\sum_{j=N_1}^{N_2}\{y(t+j) - r(t)\}^2 + \lambda\sum_{j=1}^{N_u}\{\Delta u(t+j-1)\}^2\right], \tag{21}$$

where λ denotes the user-specified parameter which means the weighting factor for the control input, and the period from N_1 thru N_2 denotes the prediction horizon, and N_u denotes the control horizon. For simplicity, they are respectively set as $N_1 = 1$, $N_2 = N$ and $N_u = N$, where N is designed in consideration of the time constant and time-delays of the controlled object.

The control law based on minimizing the cost function (21) is given by

$$\sum_{j=1}^{N} p_j F_j(z^{-1}) y(t) + \left\{ 1 + z^{-1} \sum_{j=1}^{N} p_j S_j(z^{-1}) \right\} \Delta u(t) - \sum_{j=1}^{N} p_j r(t) = 0. \quad (22)$$

$F_j(z^{-1})$ and $S_j(z^{-1})$ are calculated by the following Diophantine equations:

$$1 = \Delta \tilde{A}(z^{-1}) E_j(z^{-1}) + z^{-j} F_j(z^{-1}) \quad (23)$$
$$E_j(z^{-1}) \tilde{B}(z^{-1}) = H_j(z^{-1}) + z^{-j} S_j(z^{-1}), \quad (24)$$

where

$$E_j(z^{-1}) = 1 + e_1 z^{-1} + \cdots + e_{j-1} z^{-(j-1)} \quad (25)$$
$$F_j(z^{-1}) = f_{j,0} + \cdots + f_{j,n} z^{-n_y} \quad (26)$$
$$H_j(z^{-1}) = h_0 + h_1 z^{-1} + \cdots + h_{j-1} z^{-(j-1)} \quad (27)$$
$$S_j(z^{-1}) = s_{j,0} + \cdots + s_{j,m-1} z^{-(n_u-1)}. \quad (28)$$

Moreover, p_j is calculated by

$$[p_1, p_2, \cdots, p_N] := [1, 0, \cdots, 0] \cdot (\mathbf{H}^T \mathbf{H} + \mathbf{\Lambda})^{-1} \mathbf{H}^T. \quad (29)$$

Here, the matrix $\mathbf{H}$ which consists of coefficients of $H_j(z^{-1})$ is defined by

$$\mathbf{H} = \begin{bmatrix} r_0 & & & \\ r_1 & r_0 & \mathbf{0} & \\ \vdots & \vdots & \ddots & \\ r_N & r_{N-1} & \cdots & r_0 \end{bmatrix}, \quad (30)$$

and Λ is as follows:

$$\Lambda := \mathrm{diag}\{\lambda\}. \quad (31)$$

Here, the system parameters included in $\tilde{A}(z^{-1})$ and $\tilde{B}(z^{-1})$ are estimated by the proposed identification method.

2.5 PID parameter tuning

By replacing the coefficient polynomial of the second term (22) into the static gain, the following equation can be obtained:

$$\frac{1}{\nu} \sum_{j=1}^{N} p_j F_j(z^{-1}) y(t) + \Delta u(t) - \frac{1}{\nu} \sum_{j=1}^{N} p_j r(t) = 0, \quad (32)$$

where ν is defined as

$$\nu := 1 + z^{-1} \sum_{j=1}^{N} p_j S_j(1). \quad (33)$$

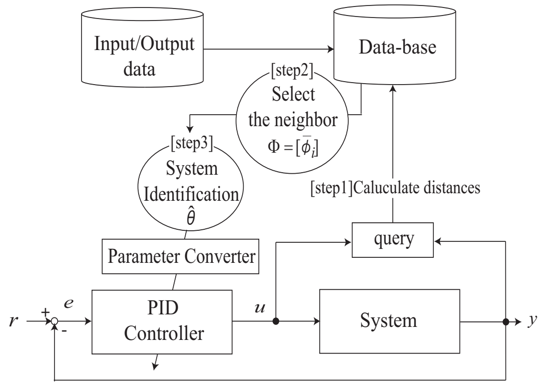

Fig. 2. Schematic figure of Data-driven system identification.

Here, the relation $\sum_{j=1}^{N} p_j F_j(1) = \sum_{j=1}^{N} p_j$ can be immediately obtained from (23). Therefore, since the following relationship is satisfied, (32) becomes identical to (20),

$$C(z^{-1}) = \frac{1}{\nu} \sum_{j=1}^{N} p_j F_j(z^{-1}). \quad (34)$$

Therefore, PID parameters can be calculated based on (20) and (34) as follows(Katayama, *et al.*, 2002):

$$\left. \begin{aligned} k_c &= -\frac{1}{\nu}(\tilde{f}_1 + 2\tilde{f}_2) \\ T_I &= -\frac{\tilde{f}_1 + 2\tilde{f}_2}{\tilde{f}_0 + \tilde{f}_1 + \tilde{f}_2} T_s \\ T_D &= -\frac{\tilde{f}_2}{\tilde{f}_1 + 2\tilde{f}_2} T_s \end{aligned} \right\}, \quad (35)$$

where $\tilde{f}_i$ is defined as

$$\frac{1}{\nu} \sum_{j=1}^{N} p_j F_j(z^{-1}) := \tilde{f}_0 + \tilde{f}_1 z^{-1} + \tilde{f}_2 z^{-2}. \quad (36)$$

Therefore, the control performance depends on the accuracy of identification and the parameter λ. In this paper, the system parameters are estimated in the system identification based on data-base, and the parameter λ is adjusted by the idea of CPA(Control Performance Assessment) to improve the accuracy of identification and the control performance.

2.6 Data-driven system identification

In recent years, development of computers enables us to memorize, fast retrieve and read out a large number of data. By these advantages, memory-based modeling (MBM) method(Takao, *et al.*, 2005) which is called *Just-In-Time* method(Zheng and Kimura, 2001) and so on has been proposed. Then, the data-based system identification scheme based on MBM is adopted in the system identification scheme of the proposed method.

In data-driven system identification, the data is stored in the data-base in the form of information vector given by (2) beforehand. Also, the information vector $\bar{\phi}(t)$, which is necessary to obtain the estimate of the output, is called '*queries*'. The algorithm of the data-driven system identification is as follows:

[STEP1] Calculate distances

Distances between the query $\bar{\phi}(t)$ and information vector $\bar{\phi}(j)(t \neq j)$ are calculated using the following $\mathcal{L}_1$ norm with some weights:

$$d(\bar{\phi}(t), \bar{\phi}(j)) = \sum_{l=1}^{3} \left| \frac{\bar{\phi}_l(t) - \bar{\phi}_l(j)}{\max_m \bar{\phi}_l(m) - \min_m \bar{\phi}_l(m)} \right|, \quad (37)$$
$$(\text{where} \quad j = 1, 2, \cdots, t-1)$$

where $t-1$ denotes the number of information vectors stored in the data-base when the query $\bar{\phi}(t)$ is given. Furthermore, $\bar{\phi}_l(j)$ denotes the l-th element of j-th information vector. Similarly, $\bar{\phi}_l(t)$ denotes the l-th element of the query. Moreover, $\max \bar{\phi}_l(m)$ denotes the maximum element among the l-th element of all information vectors ($\bar{\phi}_l(j)$, $j = 1, \cdots, k-1$) stored in data-base. Similarly, $\min \bar{\phi}_l(m)$ denotes the minimum element.

[STEP2] Select the neighbor

N_e pieces with the smallest distance are chosen from all information vectors as the neighbor.

$$\boldsymbol{\Phi} := [\ \bar{\phi}_{i_1}, \cdots, \bar{\phi}_{i_{N_e}}\ ]^T. \quad (38)$$

[STEP3] System identification

Next, using the neighbor that consisted of N_e information vectors selected in [STEP 2], the system parameter are estimated on the basis of the following weighted least squares method:

$$\bar{\theta} = (\boldsymbol{\Phi}^T \boldsymbol{V} \boldsymbol{\Phi})^{-1} \boldsymbol{\Phi}^T \boldsymbol{V} \boldsymbol{Y}, \quad (39)$$

where

$$\hat{\theta} := [\hat{a}_1, \hat{b}_0, \hat{b}_1]^T \quad (40)$$
$$\boldsymbol{Y} := [y_{i_1}, \cdots, y_{i_{N_e}}]^T \quad (41)$$
$$\boldsymbol{V} := \mathrm{diag}\{v_{i_1}, \cdots, v_{i_{N_e}}\}. \quad (42)$$

$\hat{\cdot}$ denotes an estimated value, and v_i denotes the weight corresponding to i-th information vector $\bar{\phi}(i)$ in selected neighbors. That is, the smaller the distance is, the bigger value v_i has.

[STEP4] System parameter

$\hat{T}$, $\hat{K}$ and $\hat{L}$ are computed by the following equations:

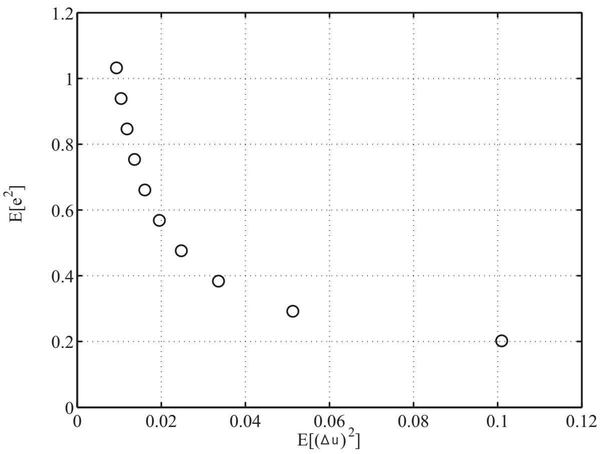

Fig. 3. Control performance trade-off curve to indicate effect of λ.

$$\hat{T} = \frac{T_s}{\log(-\hat{a}_1)} \quad (43)$$
$$\hat{K} = \frac{\hat{b}_0 + \hat{b}_1}{1 + \hat{a}_1} \quad (44)$$
$$\hat{L} = \left(\frac{\hat{b}_1}{\hat{b}_0 + \hat{b}_1} + k_m \right). \quad (45)$$

2.7 Performance-based tuning of λ

In chemical process, it is necessary to improve the productivity in consideration of saving the energy and the cost.

Then, the user-specified λ included in the GPC-PID is chosen in consideration of both the variances of control errors and the control inputs. The following relation is given by (4) and (16) when $r(t)$ is constant:

$$e(t) = -\frac{1}{D(z^{-1})}\xi(t), \quad \Delta u(t) = -\frac{C(z^{-1})}{D(z^{-1})}\xi(t), \quad (46)$$

where $C(z^{-1})$ denotes the transfer function of PID controller, and $D(z^{-1})$ is defined by

$$D(z^{-1}) := \Delta A(z^{-1}) + z^{-(k_m+1)} B(z^{-1}) C(z^{-1}). \quad (47)$$

The variances of the control errors $E[e^2(t)]$ and the incremental control inputs $E[\{\Delta u(t)\}^2]$ are computed by using H_2-norm $\|\cdot\|$:

$$\left. \begin{aligned} E[e^2(t)] &= \left\| -\frac{1}{D(z^{-1})} \right\|_2^2 \sigma_\xi^2 \\ E[\{\Delta u(t)\}^2] &= \left\| -\frac{C(z^{-1})}{D(z^{-1})} \right\|_2^2 \sigma_\xi^2 \end{aligned} \right\}, \quad (48)$$

where σ_ξ^2 denotes the variance of the modeling errors. (48) is computed using the system parameter and PID parameter.

From Fig.3, it is clear that the variances of the control errors and the control inputs are varied by changing λ. Then, in this proposed scheme, λ is determined so that the distance between the coordinate origin and a point on trade-off curve(Fig.3) becomes small.

2.8 Algorithm

The steps required in the algorithm to design the proposed performance-adaptive PID control system are as follows.

step1 The system parameters are estimated by using data-driven system identification, and the standard deviation of the prediction error, $\varepsilon(t)$, is also computed.

step2 The control performance trade-off curve as shown in Fig.3 is drawn by changing λ, where the estimates given in step1 are utilized. In addition, each variance is computed.

step3 The control weighted factor λ is determined so that the distance between the coordinate origin and a point on trade-off curve(Fig.3) becomes small.

step4 $t = t + 1$

step5 The prediction error $\eta(t)$ is calculated by

$$\eta(t) := \Delta y(t) - \bar{\phi}^T(t-1)\hat{\theta}, \qquad (49)$$

where $\hat{\theta}$ and $\bar{\phi}(t-1)$ are respectively given by the similar vectors to (40) and (8).

step6 If the following relation is satisfied, the algorithm returns to step2:

$$|\eta(t)| \geq \gamma\sigma_\varepsilon. \qquad (50)$$

If not so, go to step4. γ is set to between 3.0 and 5.0 from the viewpoint of statistics, since the prediction error for a good model is expected to be 'white'.

Using the procedure from step1 to step6, the performance-adaptive PID control system is designed. The procedure from step1 to step3 can be utilized in the initial stage of determining PID parameters.

3. SIMULATION EXAMPLE

In order to evaluate the behavior of the proposed data-driven performance-adaptive PID controller, a simulation example for a nonlinear system is considered. As a nonlinear system, the following Hammerstein model(Zi-Qiang, 1994) is discussed:

$$\left.\begin{array}{l} y(t) = 0.6y(t-1) - 0.1y(t-2) \\ +1.2x(x-k_r-1) - 0.1x(t-k_r-2) + \dfrac{\xi(t)}{\Delta} \\ x(t) = 1.5u(t) - 1.5u^2(t) + 0.5^3(t) \end{array}\right\}, \qquad (51)$$

where $\xi(t)$ denotes the white Gaussian noise with zero mean and variance 0.01^2, and $k_r = k_m = 4$ (k_r is known). The reference signals r(t) are given by:

$$r(t) = \begin{cases} 1 & (0 \leq t < 100) \\ 0.5 & (100 \leq t < 200) \\ 2 & (200 \leq t < 300) \\ 1.5 & (300 \leq t \leq 400). \end{cases} \qquad (52)$$

The information vector $\bar{\phi}$ is given by

$$\bar{\phi}(t-1) := [y(t-1), u(t-5), u(t-6)]. \qquad (53)$$

Furthermore, the user-specified parameters included in the proposed method are determined as shown in Table 1.

Table 1. User-specified parameters

The number of a data-base	$N_D = 1500$
The estimation of the time-delays	$k_m = 4$
The real time-delays	$k_r = 4$
The prediction horizon	$N = 10$
Permission rate	$\gamma = 3$

First, for the purpose of the comparison, the conventional self-tuning GPC-PID was employed. Here, the recursive LSM was used as the system identification method. The control result is shown in Fig.4, and then trajectories of PID parameters are summarized in Fig.5. From Fig.4 and Fig.5, owing to the nonlinearities, the identification accuracy and the control performance are deteriorated by the conventional GPC-PID based on the recursive LSM. Especially, the tracking property for each reference signal is different. The settling-time is relatively large in the case where the reference signal is equal to 2.0. On the other hand, the newly proposed control scheme was employed for this system. The control result by employing the proposed control scheme is shown in Fig.6, and then trajectories of PID parameters are summarized in Fig.7. From Fig.6 and Fig.7, even if the controlled system has nonlinear properties, the good control performance can be obtained using the proposed control scheme.

4. CONCLUSIONS

In this paper, the data-driven performance-adaptive PID control scheme has been newly proposed, which PID parameters are driven to the modeling performance evaluation and adjusted suitably. In other words, this paper presents a framework to

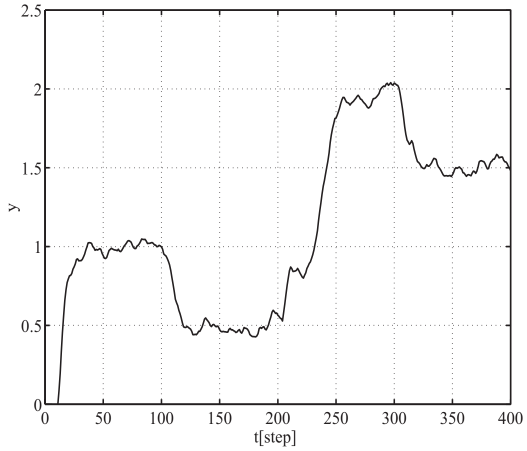

Fig. 4. Control results using the GPC-PID based on the recursive LSM.

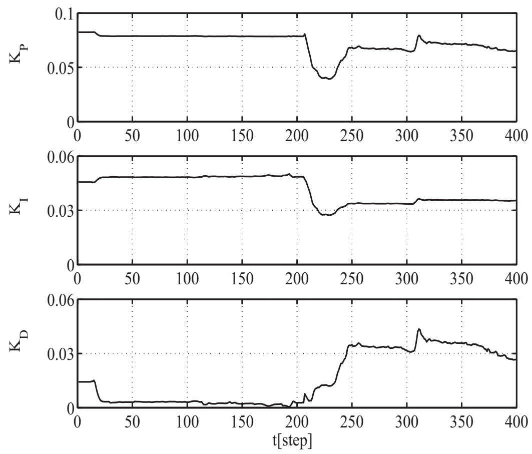

Fig. 5. Trajectories of PID parameters corresponding to Fig.4.

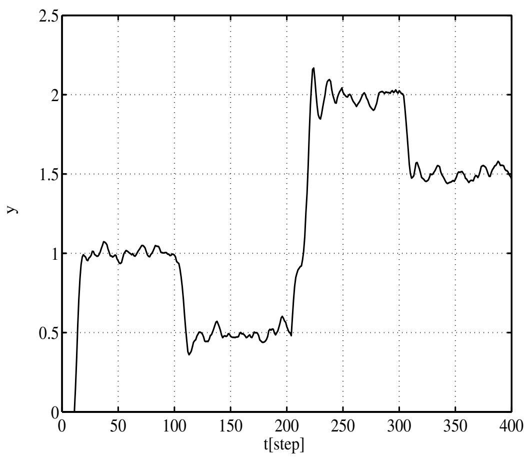

Fig. 6. Control results using the proposed control scheme.

unify the control performance and the controller design. The features of the proposed scheme are summarized as follows.

(1) The modeling performance is firstly evaluated and the system parameters are identified

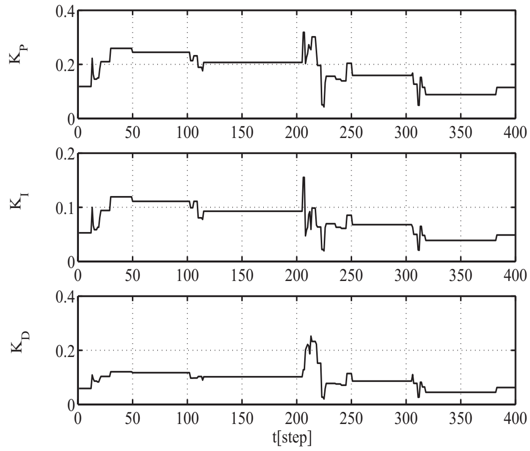

Fig. 7. Trajectories of PID parameters corresponding to Fig.6.

corresponding to the demand. In addition, PID parameters are also adjusted.

(2) A data-driven system identification is adopted in order to deal with the nonlinearity of systems.

(3) The user-specified parameter λ is chosen so that the control performance satisfies the desired performance determined beforehand.

However, the effectiveness of the proposed scheme strongly depends on the system identification as well as the conventional self-tuning PID controllers. The drastic improvement of the system identification method is required, although some strategies, *e.g.*, the identification period is introduced and the number of the estimates is reduced, have been performed in this paper. This is currently under consideration.

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