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PERFORMANCE-DRIVEN ADAPTIVE PID CONTROLLER DESIGN : THEORY AND EXPERIMENTAL EVALUATION

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Abstract: This paper proposes an adaptive PID controller which is driven by current control performance. The objective of the proposed scheme is to carry out the retuning of PID parameters and system identification only when controller performance deteriorates below a user-specified limit. Experimental evaluations on a pilot-scale process demonstrates the practicality and utility of this idea.
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Keywords: PID control, self tuning control, generalized predictive control, controller performance assessment

1. INTRODUCTION

PID control schemes based on the classical control theory, have been widely used for various process control systems for a long time. This is because PID controllers have simple control structures and, if well designed, are fairly robust and easy to understand. However, since such many industrial processes have time varying properties and changing operating regimes it is difficult to find a suitable set of PID parameters that will provide optimal process performance under all conditions. One solution for dealing with such systems is to implement self-tuning(STC) or adaptive control[1]. The basic structure of STC consists of the following steps. First, the property of the controlled system is identified by an on-line identification method such as recursive least squares. Next, the control parameters are calculated from the estimated parameters by using any one of the several PI(D) controller design algorithms. Finally, the control input is generated by the newly computed control parameters. This procedure is repeated. Clearly adaptation or auto-tuning should only be carried out only when the control performance deteriorates. It is not difficult to get an on-line measure of controller performance.[2], [3]. Many control performance assessment methods have been proposed and many instrument and control vendors have software that allows one to obtain a performance index. One of the first performance monitoring index was based on the minimum variance control benchmark based method proposed by Harris [4], [5]. The performance index in this case can be defined as the ratio of minimum variance of the closed loop output and the current actual output variance. This index can then be expressed as the value between 0 and 1. The index near 1 means good control performance, and near 0 means poor performance that may need retuning of control parameters[2]. This paper deals with the design, implementation and evaluation of an adaptive PID controller which is driven by current control performance. The calculations of the PID parameters are based on the generalized predictive control(GPC) algorithm[6]. The current control performance is obtained in an online manner over a user-specified time-window with some overlap. The retuning of PID parameters and system identification are only carried out when controller performance deteriorates below a user-specified threshold. The batch least squares identification algorithm is employed for the purpose of system identification. Input-output data from a user-specified window of the most recent record is used for identification purposes to update the process model. The new process parameters are then used to obtain a GPC-based long range predictive controller which is then approximated by a PI(D) controller [7],[8]. This paper is organized as follows: the design method of the proposed performance-driven adaptive PID controller is considered in the next section. Sections 3 and 4 evaluate the proposed method with simulation examples and experimental results followed by concluding remarks in section 5.

2. DESIGN OF PERFORMANCE-DRIVEN ADAPTIVE PID CONTROLLER

2.1 System description

In this section, the mathematical model which is important for the design of a controller is considered. In the process control scenario, many systems are typically of high order. Nevertheless it is practical to approximate such high-order processes by at most a 1st or a 2nd order systems that can capture the most dominant dynamics of the process. Such reduced order models can in turn lead to reduced-complexity controllers such as PI(D) controllers that are easier to maintain in a plant setting. In this context many STC algorithm are based on a discrete time model of the form:

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

where,

$$\left.\begin{aligned} A(z^{-1}) &= 1 + a_1 z^{-1} + a_2 z^{-2} \\ B(z^{-1}) &= b_0 + b_1 z^{-1} + \cdots + b_m z^{-m} \end{aligned}\right\} \tag{2}$$

$u(t)$ and $y(t)$ denote the control input and the corresponding output signals respectively; $\xi(t)$ denotes the white noise term; Δ is the difference operator: $\Delta = 1 - z^{-1}$, that is the process is disturbed by an integrated white noise sequence. This is a common assumption in most MPC schemes. The reason for making this assumption is that it necessitates the inclusion of an integrator in the controller based on the Internal Model Principal[9].

The controlled system based on equations (1) and (2) satisfies the following assumptions.

[Assumptions]

[A.1] a_i, b_i are unknown.
[A.2] m which is the order of $B(z^{-1})$ is known.
[A.3] $A(z^{-1})$ and $B(z^{-1})$ are irreducible or are prime with respect to each other, i.e they do not have any common factors with each other.
[A.4] The noise $\xi(t)$ satisfies the following conditions.

$$\left.\begin{aligned} &E[\xi(t)] = 0 \\ &E[\xi^2(t)] = \sigma^2 \\ &E[\xi(t)\xi(t+\tau)] = 0 \end{aligned}\right\} \tag{3}$$

[A.5] Reference signal $y_{sp}(t)$ is the piecewise constant, i.e. it is a series of steps as would be expected from a discrete system.

2.2 PID control law

The following velocity-type PID controller is employed for the controlled object given by eqn.(2):

$$\Delta u(t) = k_c \frac{T_s}{T_I} e(t) - k_c(\Delta + \frac{T_D}{T_s}\Delta^2)y(t) \tag{4}$$

where $e(t)$ denotes the control error signal given by

$$e(t) := y_{sp}(t) - y(t) \tag{5}$$

and k_c, T_I and T_D are the proportional gain, the reset time and the derivative time, respectively. And, T_s denotes the sampling interval.

For convenience, eqn.(4) is rewritten as

$$C(z^{-1})y(t) + \Delta u(t) - C(1)y_{sp}(t) = 0 \tag{6}$$

where,

$$\begin{aligned} C(z^{-1}) &= c_0 + c_1 z^{-1} + c_2 z^{-2} \\ &= k_c(1 + \frac{T_s}{T_I} + \frac{T_D}{T_s}) - k_c(1 + \frac{2T_D}{T_s})z^{-1} \\ &\quad + \frac{k_c T_D}{T_s} z^{-2}. \end{aligned} \tag{7}$$

The tuning of the control parameters included in the PID control law defined by equations (4) or (6), is important since it strongly influences the control performance. The design of this controller is based on its relation to the Generalized Predictive Control(GPC) as shown below.

2.3 Generalized Predictive Control law

Generalised Predictive Control method is one of the several variants of the popular model predictive control law and especially works well for systems with long time delays. The cost function of the Generalized Predictive Control law is defined as

$$\begin{aligned} J(t) = E[&\sum_{j=1}^{N}\{y(t+j) - y_{sp}(t)\}^2 \\ &+ \lambda \sum_{j=1}^{N}\{\Delta u(k+j-1)\}^2] \end{aligned} \tag{8}$$

where, $y_{sp}(t)$ is the reference signal; and, λ and N are the weighting factors of the control input and the prediction horizon, respectively. By minimizing the cost function of equation (8), the following GPC law can be derived,

$$\sum_{j=1}^{N} p_j F_j(z^{-1})y(t) + \{1 + z^{-1}\sum_{j=1}^{N} p_j S_j(z^{-1})\}\Delta u(t) - \sum_{j=1}^{N} p_j y_{sp}(t) = 0 \quad (9)$$

where, $F_j(z^{-1})$ can be obtained by solving the following Diophantine equation,

$$1 = \Delta A(z^{-1})E(z^{-1}) + z^{-j}F_j(z^{-1}) \quad (10)$$

$$\left.\begin{array}{l} E_j(z^{-1}) = 1 + e_{j,1}z^{-1} + \cdots + e_{j,j-1}z^{-(j-1)} \\ F_j(z^{-1}) = f_{j,0} + f_{j,1}z^{-1} + f_{j,2}z^{-2} \end{array}\right\}$$

$S_j(z^{-1})$ can be obtained by solving the following equation,

$$E_j(z^{-1})B_j(z^{-1}) = R_j(z^{-1}) + z^{-j}S_j(z^{-1}) \quad (11)$$

$$\left.\begin{array}{l} R_j(z^{-1}) = r_0 + r_1 z^{-1} + \cdots + r_{j-1}z^{-(j-1)} \\ S_j(z^{-1}) = s_{j,0} + s_{j,1}z^{-1} + \cdots + s_{j,m-1}z^{-(m-1)} \end{array}\right\} \quad (12)$$

moreover, p_j can be calculaed as:

$$[p_1, p_2, \cdots, p_N] := [1, \underbrace{0, \cdots, 0}_{N-1}](G^T G + \lambda \cdot I)^{-1} G^T \quad (13)$$

where,

$$G := \begin{bmatrix} r_0 & & & \\ r_1 & r_0 & & 0 \\ \vdots & & \ddots & \\ r_{N-1} & r_{N-2} & \cdots & r_0 \end{bmatrix} \quad (14)$$

2.4 Calculation of the PID parameters

This section discusses the calculation of the PID parameters based on GPC law [7],[8]. The GPC law (9) is rewritten by replacing the second term of the right hand side with the approximation of the static term:

$$\frac{1}{\nu}\sum_{j=1}^{N} p_j F_j(z^{-1})y(t) + \Delta u(t) - \frac{1}{\nu}\sum_{j=1}^{N} p_j y_{sp}(t) = 0 \quad (15)$$

where,

$$\nu := 1 + \sum_{j=1}^{N} p_j S_j(1) \quad (16)$$

Next, the following relation is obtained by comparing eqn.(6) and eqn.(15),

$$R_j(z^{-1}) = F_j(z^{-1}) \quad (17)$$

$$C(z^{-1}) = \frac{1}{\nu}\sum_{j=1}^{N} p_j F_j(z^{-1}) \quad (18)$$

$R_j(z^{-1})$ and $C(z^{-1})$ are designed the two control laws are equivalence. Finally, PID parameters are calculated by the following equations.

$$\left.\begin{array}{rcl} k_c &=& -\frac{1}{\nu}(\tilde{f}_1 + 2\tilde{f}_2) \\ T_I &=& -\frac{\tilde{f}_1 + 2\tilde{f}_2}{\tilde{f}_0 + \tilde{f}_1 + \tilde{f}_2} T_s \\ T_D &=& -\frac{\tilde{f}_2}{\tilde{f}_1 + 2\tilde{f}_2} T_s \end{array}\right\} \quad (19)$$

where,

$$\tilde{f}_i := \frac{1}{\nu}\sum_{j=1}^{N} p_j f_{i,j} (i = 0, 1, 2) \quad (20)$$

2.5 Current Performance Assessment

In this work, a minimum (user-specified) performance index threshold is employed to switch the adaptive function on or off. That is, the Retuning of PID parameters and system identification are only carried out when controller performance index deteriorates below a user-specified limit.

Desborough and Harris proposed the calculation method of the performance index using the minimum variance benchmark for the closed loop system. In this paper, the performance index is defined slightly differently as in [2]:

$$\eta(t) = \frac{\sigma^2{}_{mv}(t)}{\sigma^2{}_e(t)} \quad (21)$$

where,$\sigma^2{}_e(t)$, $\sigma^2{}_{mv}(t)$ correspond to the variance of control error signal and minimum variance of closed loop system respectively. These signals are computed over a moving window of past data where the width of the window, twin, is specified by the user. Thw control performance metric can be calculated in an online manner with or without overlap between each data window.

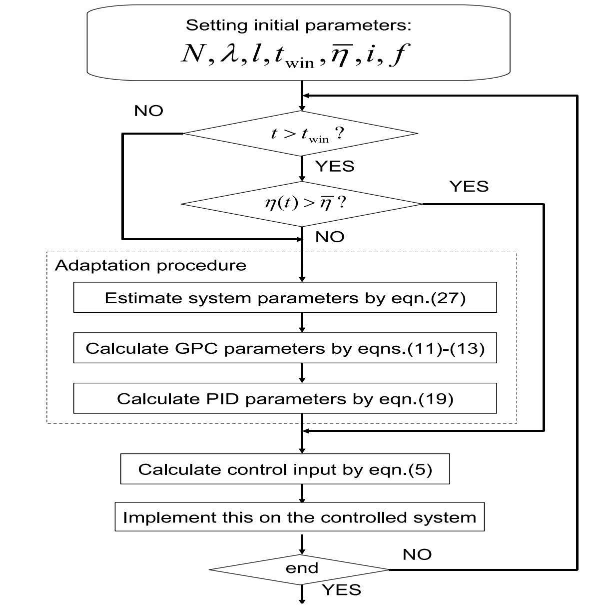

Fig. 1. Algorithm of the proposed method.

2.6 System Identification Method

The recursive least squares method (RLS) has been a popular estimation method for the self-tuning controller. However, RLS requires the parameter estimation at every step. In this work, the estimation is carried out only on demand or when required or intermittently based on the current performance index(21). So, the batch type least squares method is employed.

$\hat{\theta}(t)$ is the estimates of the unknown parameters $\theta = [a_1, b_0, \ldots, b_m]^T$

$$\hat{\theta}(t) = [\hat{a}_1(t), \hat{a}_2(t), \hat{b}_0(t), \ldots, \hat{b}_m(t)]^T \quad (22)$$

First, the following first order filer is used for input and output signals.

$$y_f(t) = \frac{1-f}{1-fz^{-1}} y(t) \quad (23)$$

$$u_f(t) = \frac{1-f}{1-fz^{-1}} u(t) \quad (24)$$

Next, the data matrix is configured as:

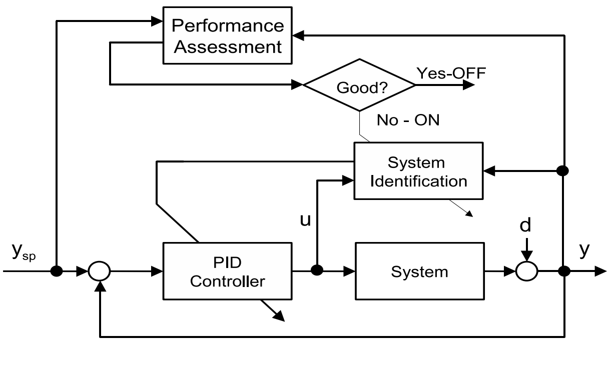

Fig. 2. Block diagram of the proposed method.

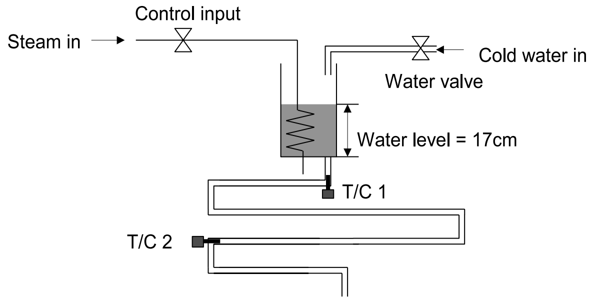

Fig. 3. Tank heater equipment.

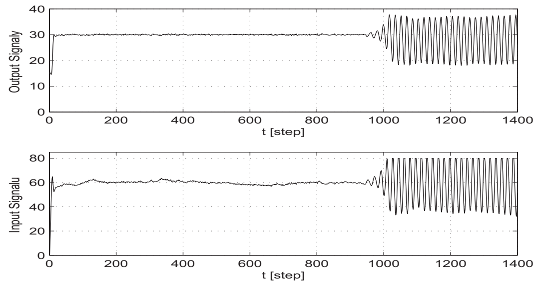

Fig. 4. Input and output time-series under fixed PI control.

$$Z(t) = \begin{bmatrix} -\Delta y_f(t-1) & -\Delta y_f(t-2) & \Delta u_f(t-1) & \cdots \Delta u_f(t-m-1) \\ -\Delta y_f(t-2) & -\Delta y_f(t-3) & \Delta u_f(t-2) & \cdots \Delta u_f(t-m-2) \\ \vdots & \vdots & \vdots & \ddots \quad \vdots \\ -\Delta y_f(t-l) & -\Delta y_f(t-l-1) & \Delta u_f(t-1) & \cdots \Delta u_f(t-m-l) \end{bmatrix} \quad (25)$$

where, l is the length of the data window for estimation. And, the output vector is defined as:

$$\mathbf{y}(t) = [\Delta y_f(t), \Delta y_f(t-1), \cdots, \Delta y_f(t-l)]^T \quad (26)$$

The estimated system parameter vector is calculated from the following equation.

$$\hat{\theta}(t) = \{Z^T(t)Z(t)\}^{-1} Z(t)^T \mathbf{y}(t) \quad (27)$$

Recursive least squares is employed initially for $t < l$, because enough data may not be available for batch type identification.

After the initialization step, the identification is only carried out when controller performance deteriorates below a user-specified limit $\bar{\eta}$. So, PID parameters calculation based on GPC is also done when the performance index is under $\bar{\eta}$. The algorithm of proposed scheme is summarized in Fig. 1. And, the block diagram of proposed scheme is also shown in Fig. 2.

3. PERFORMANCE-DRIVEN ADAPTIVE PID CONTROL OF A TANK HEATER

In this section, the practically and utility of proposed method is discussed through the experimental evaluation of the tank heater.

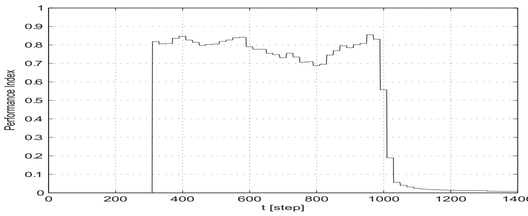

Fig. 5. Performance index time-series under fixed PI control.

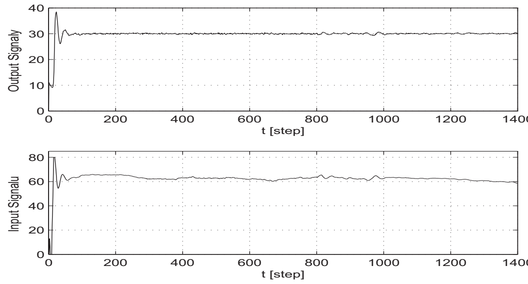

Fig. 6. Input and output time-series under auto-tuned PI control.

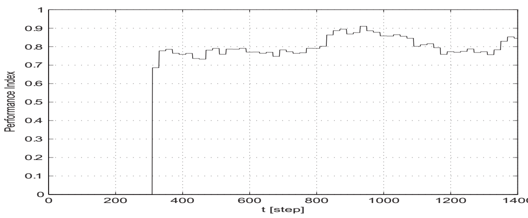

Fig. 7. Performance index time-series under auto-tuned PI control.

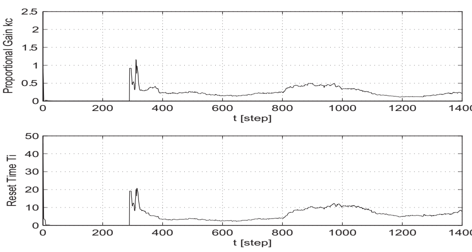

Fig. 8. Trajectory of PI parameters of the auto-tuned PI controller.

The tank heater equipment is illustrated in Fig.3. The water level is regulated at 17[cm] by another level control loop. The experimental time is 14000[s]. The control input is shown in terms of % opening of the steam valve. The system output is obtained from T/C1(thermocouple 1) and T/C2. T/C1 is used for the first 8000s and thereafter the feedback sensor is switched to T/C 2. With the feedback sensor switched to T/C2, the time delay increases substantially causing the fixed PI controller to become unstable. In earlier study [10], the transfer functions for each thermocouples were obtained n a previous study. [6]. The transfer function between T/C1 and the steam flow rate is

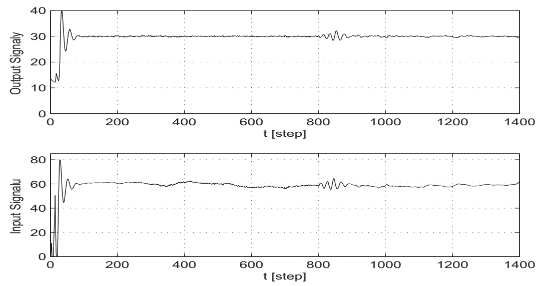

Fig. 9. Input and output results of the performance-driven PI controller.

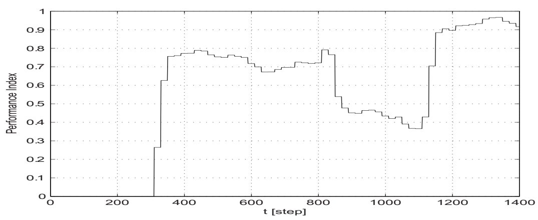

Fig. 10. Performance index of the performance-driven PI controller.

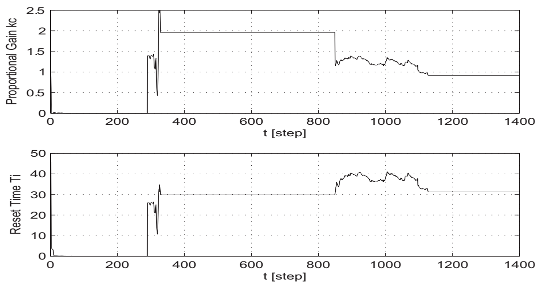

Fig. 11. Trajectory of PI parameters of the performance-driven PI controller.

$$G(s) = \frac{0.67}{53s+1}e^{-7.8s} \tag{28}$$

and, the transfer function between T/C2 and the steam flow rate is

$$G(s) = \frac{0.67}{73s+1}e^{-49s} \tag{29}$$

The sample time of 10[s] used represents approximately 1/7-1/5 of the process time constant. The PI controller is employed because this process property can be sufficiently well approximated by a first order system.

Process transfer function shown in eqn. (28) was only used in the design of the fixed PI controller. It is important to also note the significant change in the delay due to the change in the thermocouple. First, the fixed PI controller was employed for this process. The PI parameters were calculated as:$k_c = 1.9347, T_I = 30.7566$ from eqn.(19) using the discretized parameters of eqn.(28).

Fig. 4 shows the input and output results of the fixed PI controller. The corresponding control performance index is shown as Fig. 5. Because of the time-delay change, this controller renders the system unstable after 8000. Naturally the performance index is deteriorates to a low level (see Figure 5). This control performance index is calculated every 10 samples from an overlapping moving window of 300 samples.

Next, the conventional self-tuning PI controller which uses batch type least squares identification is employed. The equivalent model used for system identification is:

$$\hat{y}(t) = -\hat{a}_1 y(t-1) + \hat{b}_0 u(t-1) + \hat{b}_1 u(t-2) + \hat{b}_2 u(t-3) + \hat{b}_3 u(t-4) + \hat{b}_4 u(t-5). \quad (30)$$

The parameters in eqn.(30) are identified from the last 300 samples of input and output data. The PI parameters are retuned at every sample based on eqn.(19) with the estimates obtained in eqn.(30). Figs.6 and 7 show the input and output results and control performance index with the self-tuning PI controller. In contrast to figure 4, these results show how satisfactory performance can be maintained even when the process parameters (in this case the time delay and the time constant) change significantly. However, Fig.8 which shows the trajectory of PI parameters calculation indicates that needless retuning is being carried out during the period even when performance is relatively good.

Finally, Figs.9, 10 and 11 show the input and output results, control performance index and the trajectory of PI parameters, respectively, by using the proposed performance driven PI controller. The PI parameters retuning is carried out only when the current control performance drops below the user-specified threshold limit of 0.6.

The input and output signals become oscillatory at $t = 800$, because of the increase in the time delay. This change results in a degraded performance as can be seen in figure 10. Fig. 11 indicates that parameters identification and retuning of PI parameters commenced only when the performance index decreased below 0.6. This retuning enhances the performance index after about $t = 1100$.

4. CONCLUSIONS

In this paper, an adaptive PID controller, driven by a control performance loop, has been considered. First, a self-tuning PID controller based on the GPC law is constructed by using batch type LS. Retuning and identification of this controller are only carried out when controller performance deteriorates below a user-specified limit.

The proposed scheme can be termed as pseudo-adaptive or on-demand adaptive controller in the sense that adaptation is only carried out when necessary. Performance evaluation can be carried out over a moving window with or without overlaps depending on the computational loads that can be sustained by a DCS system. The practicality and utility of the proposed system has been shown to by experimental evaluation.

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