Model-Based Autotuning System with Two-Degree-of-Freedom Control

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Abstract

A model-based autotuning system with two-degree-of-freedom (2-df) control is presented. This 2-df control system presented provides capabilities of set-point tracking and load rejection as well in one single system and the two control objectives can be considered independently for design. A closed-loop system is presented to generate an excitation input sequence for system identification. The closed-loop system aforementioned consists of an control algorithm to eliminate unknown but constant disturbances during identification and guarantee the input to have a zero mean. The identification method is derived from an intermediate stage of the sub-space identification algorithm. From which, an impulse response sequence of the process can be computed and a reduced order model is then identified. The effectiveness of this proposed 2-df autotuning system is demonstrated with simulation results.

1. Introduction

Autotuning of PI/PID controllers using relay feedback [1] becomes popular nowaday. It includes estimations of ultimate gain and ultimate frequency or even parameters of transfer function model [3] to apply to different tuning methods. Regarding the controller design or tuning in these autotuning systems found in literature, the resulting system cannot be optimal for both set-point tracking and disturbance rejection simultaneously in one simple feedback system. Therefore, in the design of a conventional feedback control system, a compromise has to be made between the set-point tracking performance and disturbance rejection performance because these two objectives are conflicting. Unfortunately, the trade-off between them is not easily made due to the lack of clear and simple criterion. To overcome the difficulty and improve the control performance, a control system with two-degree-of-freedom (2-df) can be used. For example, Tian and Gao [7] proposed a double-controller scheme, where a controller for set-point following and a controller for disturbance rejection can be designed independently. Although their system is theoretically sound, a major drawback of Tian and Gao's system is the complexity of the system in implementation.

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In this paper, a new model-based 2-df controller design is presented. The 2-df controllers are similar to the double-controller of Tian and Gao [7] but simpler and has very clear link to the identification of dynamic model and the objectives of the control. In order to identify the model, an excitation input sequence similar to the pseudo-random binary signal (PRBS) is used to activate the process under closed-loop. The excitation input is generated under a proposed closed-loop, which monitors the mean of the outputs to compensate for unknown but constant disturbances during the identification stage. Using the collected input and output data, the identification algorithm is derived from an intermediate result of the sub-space identification method [8]. From which, a sequence of impulse response of the open-loop process can be obtained and a reduced order model in terms of FOPDT or SOPDT dynamics can be identified. Based on the identified model, a 2-df control structure simpler than the double-controller scheme of Tian and Gao [7] is proposed. The effectiveness of this proposed autotuning system will be demonstrated with simulated examples.

2. 2-df control structure

The structure of proposed 2-df control system is as

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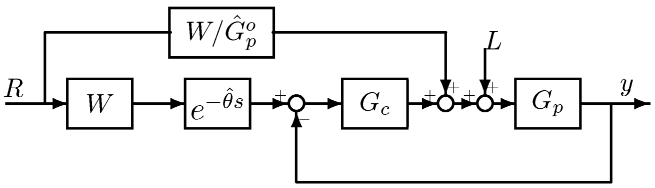

Figure 1: *The two-degree-of-freedom control system*

shown in Fig. 1 where $G_p(s)$, $G_c(s)$ and $W(s)$ designate the transfer functions of process, controller and desired set-point response, respectively. Also, $\hat{G}_p(s)$ designates the process model and $\hat{G}_p(s) = \hat{G}_p^o(s)\ e^{-\hat{\theta}s}$ where $\hat{G}_p^o(s)$ is the delay-free portion of the model.

In the structure of Fig. 1, the set-point R has two paths to the feedback loop. One passes through $W(s)$ and a dead time of the model to become the actual set-point of the feedback loop. The other path passes through $W(s)/\hat{G}_p^o(s)$ and then is added to the controller output. Thus, the closed-loop responses for set-point (R) and load input (L) can be written as:

$$\frac{y}{R} = \frac{W(s)G_c(s)G_p(s)e^{-\hat{\theta}s}}{1+G_c(s)G_p(s)} + \frac{W(s)G_p(s)}{[1+G_c(s)G_p(s)]\hat{G}_p^o(s)} \tag{1}$$

$$\frac{y}{L} = \frac{G_p(s)}{1+G_c(s)G_p(s)} \tag{2}$$

It can be seen from Eq.(2) that the load response of the closed-loop system is determined only by the controller G_c and has been separated from the set-point response. Therefore, the controller can be designed independently to achieve optimal performance for disturbance rejection (e.g. minimization of performance index such as IAE, ISE, ITAE, $\cdots$).

Regarding the set-point response, from Eq.(1) and with a perfect process model (i.e. $G_p(s) = \hat{G}_p^o(s)e^{-\hat{\theta}s}$), it becomes:

$$\begin{aligned}\frac{y}{R} &= \frac{W(s)G_c(s)G_p(s)e^{-\hat{\theta}s}}{1+G_c(s)G_p(s)} + \frac{W(s)e^{-\hat{\theta}s}}{1+G_c(s)G_p(s)} \\ &= W(s)e^{-\hat{\theta}s}\end{aligned} \tag{3}$$

Equation (3) clearly indicates that the set-point response is independent of the controller $G_c(s)$ and, after the process dead time, can be assigned as any desired response by specifying $W(s)$. Theoretically, the desired set-point response, $W(s)$, can be arbitrarily given. However, in order to make $W(s)/\hat{G}_p^o(s)$ be practically realizable, the order of $W(s)$ cannot be smaller than that of $\hat{G}_p^o(s)$.

With the proposed control structure, the control of set-point tracking and disturbance rejection can be designed individually, and achieving optimal performance for both objectives becomes possible. Furthermore, with a good process model, the set-point response thus obtained is similar to that resulted from Smith predictor design [5] so that the process dead time can be effectively compensated. An inherent drawback of the Smith predictor is its performance sensitivity to the process model. As we will show below, the proposed 2-df control structure is not only very effective, but also more robust than the Smith predictor.

To demonstrate the effectiveness and robustness of this 2-df control structure, consider a process of $G_p(s) = e^{-2s}/(s+1)$. To design the 2-df control, the desired set-point response is picked as $W(s) = 1/(s+1)$. In addition, the controller G_c used in the feedback loop is a series PID controller tuned by minimum IAE formula for disturbance rejection [4], which results in $k_c = 0.69$, $\tau_R = 1.54$ and $\tau_D = 0.70$. On the other hand, in the Smith predictor design using direct synthesis method, this desired set-point transfer function leads to a PI controller with $k_c = 1$ and $\tau_R = 1$. A unit step change in set-point at $t = 0$ and a unit negative step change in load disturbance at $t = 20$ are introduced as excitation signals. Figure 2(a) shows the responses of these two control schemes with a perfect process model. As the way they have been designed, the set-point responses of the two systems overlap each other. Moreover, the load response of the 2-df control system is better than that of the Smith predictor. To simulate the process uncertainty, assume the steady-state gain of the process deviate from its nominal value of 1 to 0.7 and all the controller settings are kept unchanged. Figure 2(b) shows the resulting responses of these two control schemes. The 2-df control structure has much superior responses for both set-point tracking and disturbance rejection than those of the Smith predictor, indicating that the proposed 2-df control structure is less sensitive to model error.

3. Identification of process model

To apply the 2-df control structure as shown in Fig. 1 presented in the previous section, a model of the process is required. Usually, high-order processes are represented as reduced order dynamic models such as first-order-plus-dead-time (FOPDT) and second-order-plus-dead-time (SOPDT) for simplicity. In addition, higher-order process models are not suitable for the proposed 2-df design because, if a high-order model is used, the $W(s)$ has also to be high-order so that the set-point response will be very sluggish. Therefore, a method for the identification of reduced order process model is presented in this section. This proposed method identifies the model through estimation of impulse response sequence of the process, where the algorithm is derived from an

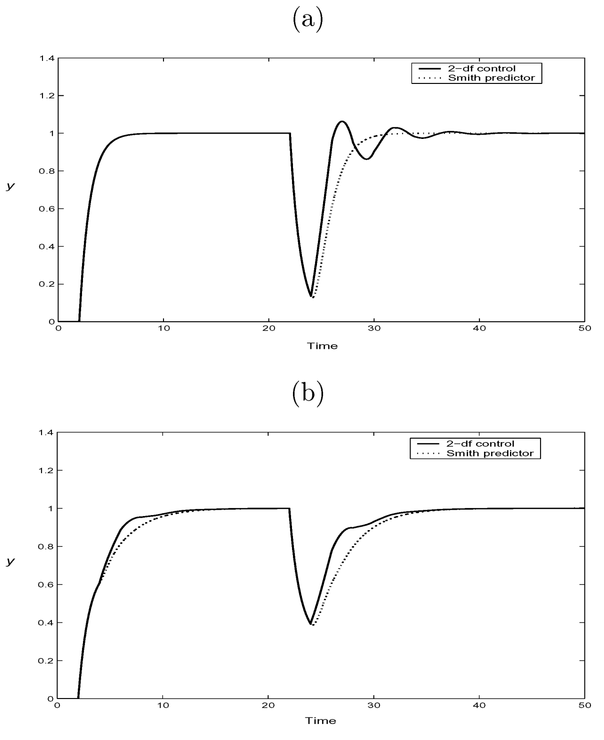

Figure 2: *Comparisons of control performance (a) perfect process model (b) process gain deviating from 1 to 0.7*

intermediate result of the sub-space identification method. The details are described as the following.

3.1 Estimation of impulse response sequence

The identification of a dynamic system is to find a sequence of $h(i)$ so that the output of the system can be expressed as a sum of moving averages from the input as the following.

$$y(k) = \sum_{i=-\infty}^{k} h(k-i)u(i) \tag{4}$$

where y and u denote the system output and input, respectively. This sequence of $h(i)$, $i = 0, 1, 2, \cdots$ is called as impulse response sequence or weighting sequence. For open-loop stable system, this sequence will decay to zero after some $i > p$ and the system output can be expressed as:

$$y(k) = \sum_{i=k-p}^{k} h(k-i)u(i) \tag{5}$$

There are a number of obvious advantages of the impulse response sequence model from the viewpoint of system identification [2]. For example, the determination of the impulse response sequence requires less *a prior* knowledge than do the parametric models, and this model can be identified more satisfactorily in the presence of noise. The typical method for identifying the impulse response sequence is the least-squares estimation. First, the input $u(t)$ is used to continuously drive the system and the sampled input sequence $\{u(i)\}$, for $0 \leq i \leq m+p$ where $m > p$, and output sequence $\{y(i)\}$, for $p \leq i \leq m+p$, are collected. Then, using the observed input-output data in Eq.(5), one can set up a set of $m+1$ equations written in the vector form as:

$$\mathbf{y} = \mathbf{U}\mathbf{h} \tag{6}$$

where

$$\begin{aligned} \mathbf{y} &= [y(p),\ y(p+1),\ \cdots,\ y(p+m)]^T \\ \mathbf{h} &= [h(0),\ h(1),\ \cdots,\ h(p)]^T \\ \mathbf{U} &= \begin{bmatrix} u(p) & u(p-1) & \cdots & u(0) \\ u(p+1) & u(p) & \cdots & u(1) \\ \vdots & \vdots & \ddots & \vdots \\ u(p+m) & u(p+m-1) & \cdots & u(m) \end{bmatrix} \end{aligned} \tag{7}$$

Thus, the unknown parameter vector $\mathbf{h}$ can be estimated by the method of least-squares as:

$$\mathbf{h} = (\mathbf{U}^T\mathbf{U})^{-1}\mathbf{U}^T\mathbf{y} \tag{8}$$

However, before proceeding the estimation, the value of settling time parameter p must be chosen in advance. To obtain the accurate result, p should be picked according to the condition $h(i > p) \approx 0$, which may result in some complexities of computation. Because, usually, we may repeat the solution with progressively increasing p values until a satisfactory fit has been achieved. However, a large p increases the computational difficulties associated with high order matrix inversion in Eq.(8).

To overcome computational difficulties mentioned earlier, an alternative algorithms is then presented to identify the impulse response sequence. The main idea is that the future output can be represented by the past input, past output and future input. First, let the time before and after sampling instant m be referred as past and future, respectively. Then, given recorded process inputs and outputs, the Hankel matrices of past input ($\mathbf{U}^p$), past output ($\mathbf{Y}^p$), future input ($\mathbf{U}^f$), and future output ($\mathbf{Y}^f$) can be written as:

$$\mathbf{U}^p = \begin{bmatrix} u(0) & u(1) & \cdots & u(n-1) \\ u(1) & u(2) & \cdots & u(n) \\ \vdots & \vdots & \ddots & \vdots \\ u(m-1) & u(m) & \cdots & u(m+n-2) \end{bmatrix} \tag{9}$$

$$\mathbf{Y}^p = \begin{bmatrix} y(0) & y(1) & \cdots & y(n-1) \\ y(1) & y(2) & \cdots & y(n) \\ \vdots & \vdots & \ddots & \vdots \\ y(m-1) & y(m) & \cdots & y(m+n-2) \end{bmatrix} \tag{10}$$

$$\mathbf{U}^f = \begin{bmatrix} u(m) & u(m+1) & \cdots & u(m+n-1) \\ u(m+1) & u(m+2) & \cdots & u(m+n) \\ \vdots & \vdots & \ddots & \vdots \\ u(2m-1) & u(2m) & \cdots & u(2m+n-2) \end{bmatrix} \tag{11}$$

$$\mathbf{Y}^f = \begin{bmatrix} y(m) & y(m+1) & \cdots & y(m+n-1) \\ y(m+1) & y(m+2) & \cdots & y(m+n) \\ \vdots & \vdots & \ddots & \vdots \\ y(2m-1) & y(2m) & \cdots & y(2m+n-2) \end{bmatrix} \tag{12}$$

where $n \gg m$. As a result, the predicted future output can be represented as:

$$\hat{\mathbf{Y}}^f = [\mathbf{\Theta}^{\mathbf{U}^p} \quad \mathbf{\Theta}^{\mathbf{Y}^p} \quad \mathbf{\Theta}^{\mathbf{U}^f}] \begin{bmatrix} \mathbf{U}^p \\ \mathbf{Y}^p \\ \mathbf{U}^f \end{bmatrix} \tag{13}$$

The parameter matrix $[\mathbf{\Theta}^{\mathbf{U}^p} \quad \mathbf{\Theta}^{\mathbf{Y}^p} \quad \mathbf{\Theta}^{\mathbf{U}^f}]$ is found to minimize the prediction error of $||\mathbf{Y}^f - \hat{\mathbf{Y}}^f||^2$ and its least-squares solution is given as the following:

$$[\mathbf{\Theta}^{\mathbf{U}^p} \quad \mathbf{\Theta}^{\mathbf{Y}^p} \quad \mathbf{\Theta}^{\mathbf{U}^f}] = \mathbf{Y}^f \mathbf{X}^T (\mathbf{X}\mathbf{X}^{\mathbf{T}})^{-1} \tag{14}$$

where

$$\mathbf{X} = \begin{bmatrix} \mathbf{U}^p \\ \mathbf{Y}^p \\ \mathbf{U}^f \end{bmatrix} \tag{15}$$

It is found that $\mathbf{\Theta}^{\mathbf{U}^f}$ thus obtained is a lower block triangular Toeplitz matrix as the following:

$$\begin{aligned} \mathbf{\Theta}^{\mathbf{U}^f} &= \left[\theta_{i,j}^{\mathbf{U}^f}\right]_{i,j=1,2,\cdots,m} \\ &= \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ z_1 & 0 & 0 & \cdots & 0 \\ z_2 & z_1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ z_{m-1} & z_{m-2} & \cdots & z_1 & 0 \end{bmatrix} \end{aligned} \tag{16}$$

In fact, by following the N4SID algorithm [8] of subspace identification, a state space process model $(\mathbf{A}, \mathbf{B}, \mathbf{C})$ can be obtained. It is interesting to find that each z_i in Eq.(16) equals $\mathbf{CA}^{i-1}\mathbf{B}$ from N4SID. Notice that the impulse response sequence satisfies $h(i) = \mathbf{CA}^{i-1}\mathbf{B}$, $i = 1, 2, \cdots,$ for linear dynamic system. In other words, the sequence of $\{z_i\}$ forms the initial part of impulse response sequence of the system. As a result, the impulse response sequence in Eq.(5) is then taken as the first column of $\mathbf{\Theta}^{\mathbf{U}^f}$, that is:

$$\{h(i)\} = \theta_{i+1,1}^{\mathbf{U}^f} \qquad i = 0, 1, 2, \cdots, m-1 \tag{17}$$

With the initial portion of the impulse response sequence from Eq.(17), a reduced order transfer function model in terms of FOPDT or SOPDT of the following can be found.

$$\begin{aligned} \text{FOPDT} \qquad \hat{G}_p(s) &= \frac{k_p \, e^{-\theta s}}{\tau s + 1} \\ \text{SOPDT} \qquad \hat{G}_p(s) &= \frac{k_p \, e^{-\theta s}}{(\tau_1 s + 1)(\tau_2 s + 1)} \end{aligned} \tag{18}$$

For FOPDT model, the impulse response sequence, after transient response, will decay with a constant ratio, designated as ϕ. Thus, we have:

$$\frac{h(i)}{h(i-1)} = \phi = e^{-T_s/\tau} \tag{19}$$

where T_s is the sampling interval. For SOPDT model, the impulse response sequence satisfies the following relation after transient response.

$$h(i) = \phi_1 \, h(i-1) + \phi_2 \, h(i-2) \tag{20}$$

where

$$\begin{aligned} \phi_1 &= e^{-\frac{T_s}{\tau_1}} + e^{-\frac{T_s}{\tau_2}} \\ \phi_2 &= -e^{-\frac{T_s}{\tau_1}} e^{-\frac{T_s}{\tau_2}} \end{aligned} \tag{21}$$

Consequently, the value of ϕ or ϕ_1, ϕ_2 can be computed from Eq.(19) or Eq.(20) using the initial portion of the impulse response sequence in Eq.(17). Furthermore, the time constant(s) of the model can be calculated by Eq.(19) or Eq.(21) and the remaining portion of the impulse response sequence is estimated using Eq.(19) or Eq.(20). Calculation of the impulse response sequence in this way can efficiently reduce the dimension of the matrix in Eq.(14). After the entire impulse response sequence is obtained, the steady-state process gain is the summation of each weighting value as:

$$k_p = \sum_{i=0}^{p} h(i) \tag{22}$$

Also, the dead time for FOPDT model can be computed by:

$$\theta = \int_0^\infty \left(1 - \frac{y_s(t)}{k_p}\right) dt - \tau \tag{23}$$

or, for SOPDT model,

$$\theta = \int_0^\infty \left(1 - \frac{y_s(t)}{k_p}\right) dt - \tau_1 - \tau_2 \tag{24}$$

where $y_s(t)$ is the unit step response of the process and its sampled data is computed from:

$$y_s(i) = \sum_{j=0}^{i} h(j) \tag{25}$$

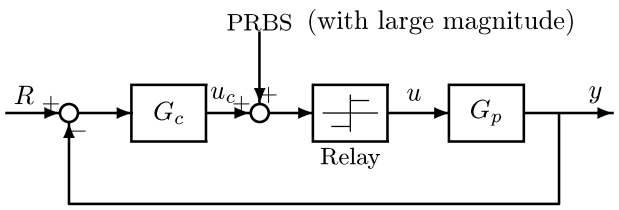

Figure 3: *The closed-loop scheme for identification*

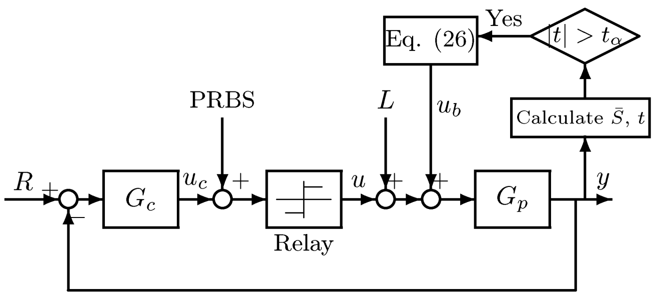

Figure 4: *The adaptive scheme for identification under unknown disturbance*

3.2 Generation of excitation inputs for closed-loop identification

To use this proposed least-squares method for computing the impulse response sequence, the result is accurate only when the input signal, $u(i)$, is uncorrelated. It is straightforward that one can introduce a white random noise to activate the process under open-loop for the identification. However, process activation under closed-loop is usually desirable to prevent process output drifting away from its normal operation range due to unknown disturbances. Therefore, a closed-loop scheme to generate excitation input signal is presented as shown in Fig. 3 for this identification. Although the scheme shown in Fig. 3 is the conventional feedback system, it can be directly applied to the 2-df structure shown in Fig. 1.

In Fig. 3, a pseudo-random binary signal (PRBS) is added to the controller output u_c. The magnitude of this PRBS introduced should be large enough so that its sign will not changed by the controller output. Then, the resulting signal is passed through a relay element before it enters the process. As a result, the process input, u, is still similar to a PRBS with magnitude $\pm a$ where a is the height of relay. With this structure, random input to the process can be generated under closed-loop operation and the identification method aforementioned can then applied.

3.3 Adaptation to unknown disturbance

During the identification stage, unknown disturbance could cause significant error in the identification result. This error will in turn degrade the closed-loop performance. ThereforAdaptation to unknown disturbance a complete autotuning system should include the mechanism to eliminate the identification error caused by unknown disturbance. To eliminate the effect of unknown but constant disturbance, a bias value, u_b, is introduced to the process input when the unknown disturbance is detected. In other words, the relay is shifted vertically by this bias value. A feedback method to automatically update the bias value is presented as the following.

Denote the integral of the process output over a period P as S, i.e. $S = \int_t^{t+P} y(t)dt$. Because the process is activated by a PRBS, the average value of S, designated as $\bar{S}$, over several successive periods should approach zero if there is no unknown disturbance. Based on this hypothesis, the Student t statistic is then applied for testing the $\bar{S}$. Once the value of t statistic falls outside the prescribed significance level, t_α (e.g. $\alpha = 5\%$), the above hypothesis is rejected and it is recognized that some unknown disturbance has happened to the system. In case of $k_p > 0$, $\bar{S} > 0$ ($\bar{S} < 0$) implies that a positive (negative) disturbance has happened and, hence, a negative (positive) bias has to be introduced. The adverse results can be concluded for the case of $k_p < 0$. According to the analysis, the introduced bias value has to be updated to eliminate the effect of disturbance by the following rule:

$$u_b^i = u_b^{i-1} - \text{sign}(k_p)\gamma\bar{S} \tag{26}$$

where $\gamma > 0$ is the convergence rate. This adaptive mechanism is shown graphically in Fig. 4. Such adaptation of u_b can make the process output oscillate around its steady-state value automatically under unknown but constant disturbance so that the proposed autotuning can be proceeded successfully.

4. Illustrative examples

4.1 Example 1. FOPDT process

To show the procedures of proposed identification method, consider the same FOPDT process described in section 2. By the scheme of Fig. 3, a PRBS with large magnitude is introduced to excited the system and the relay height is set as 1 so that the process input u is similar to a PRBS with magnitude ± 1. Meanwhile, the process input and output are collected with sampling interval $T_s = 0.5$. The parameters for estimating the impulse response sequence are chosen as

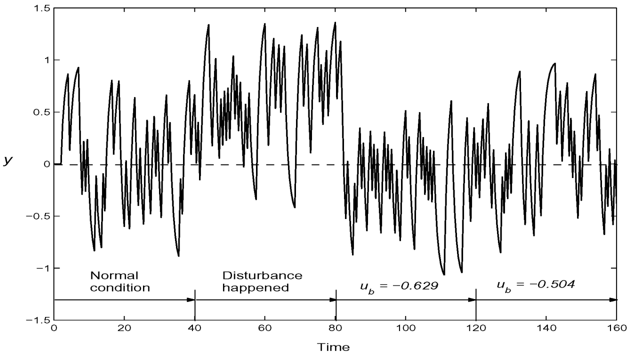

Figure 5: *Process output in example 1*

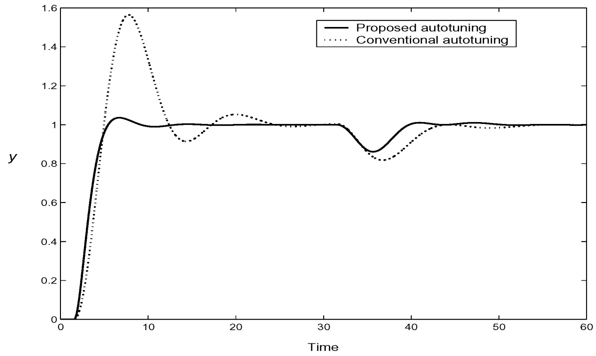

Figure 6: *Closed-loop responses in example 2*

$m = 8$ and $n = 61$, which means that the data from $t = 0$ to $t = 37$ are used for identification. The initial portion of impulse response sequence estimated is $\mathbf{h} = [0\ 0\ 0\ 0\ 0\ 0.3935\ 0.2387\ 0.1447]$, which implies that the process belongs to FOPDT dynamics with $\phi = 0.6065$ (or $\tau = -T_s/\ln\phi{=}1$). Then, the entire impulse response sequence is calculated and the model is identified as $\hat{G}_p(s) = e^{-2.02s}/(s+1)$, which is almost identical to the real process.

Assume, at $t = 40$, a step disturbance of magnitude 0.5 happened to the system. According to the scheme shown in Fig. 4, this disturbance is detected from the t statistic of $\bar{S}$ and then the bias u_b has to be updated using Eq.(26). Choosing $\gamma = 0.15$, the value of u_b is converged after two iterations and its final value is -0.504. The whole process output in this experiment is as shown in Fig. 5. Then, the data collected after $t = 120$ are used for identification again and the resulting model is $\hat{G}_p(s) = 1.002e^{-2.025s}/(1.004s+1)$. This result indicates that the proposed identification method performs well even under the presence of unknown disturbance.

4.2 Example 2. Third-order process

Consider a third-order process of the following:

$$G_p(s) = \frac{e^{-1.5s}}{(s^2+10s+1)(2s+1)}$$

For system identification, the same experiment as that in example 1 is conducted. In addition, the parameters for estimation of impulse response sequence are chosen as $m = 18$ and $n = 140$. As a result, the initial portion of impulse response sequence estimated is $\mathbf{h} = [0\ 0\ 0\ 0\ 0.0044\ 0.0137\ 0.0209\ 0.0260\ 0.0295\ 0.0317\ 0.0330\ 0.0336\ 0.0337\ 0.0334\ 0.0328\ 0.0320\ 0.0310\ 0.0300]$. It is found that this process can be represented by a SOPDT model with $\phi_1 = 1.727$ and $\phi_2 = -0.738$, or $\tau_1 = 9.88$ and $\tau_2 = 1.98$. Then, the whole impulse response sequence is calculated and the model is identified as $\hat{G}_p(s) = 0.998\ e^{-1.57s}/[(9.88s+1)(1.98s+1)]$.

Based on this identified model, the 2-df control structure is applied accordingly. The desired set-point response is picked as $W(s) = 1/(s^2+1.6s+1)$ which is slightly underdamped to speed the response. For disturbance rejection, an ideal PID controller is used in the feedback loop and is tuned according to minimum ITAE formula [6], which gives $k_c = 8.18$, $\tau_R = 4.38$ and $\tau_D = 1.70$. Figure 6 shows the closed-loop responses of this 2-df control system and also the conventional PID autotuning system of Åström and Hägglund [1] for comparison. It can be seen that both performances for set-point tracking and disturbance rejection of the proposed autotuning system are satisfactory.

5. Conclusions

A model-based autotuning system with 2-df control has been proposed in this paper. For system identification, a closed-loop scheme is devised to generate an excitation input similar to a PRBS to estimate the impulse response sequence of the process and then its low-order model is identified accordingly. This identification can be done under closed-loop operation as well as under the presence of unknown but constant disturbances. Based on the identified model, a 2-df control structure is presented to separate the controller design for disturbance rejection from that for set-point tracking in a closed-loop system. The inevitable compromise between these two performances in the conventional feedback system is no longer necessary. With this structure, the disturbance rejection performance can be optimized by designing the controller in the feedback loop, and the set-point response can be independently specified where the advantage of dead time compensation can also be taken. The simulation results have shown that this proposed autotuning system is efficient and self-contained.

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