NONCAUSAL OPEN-LOOP CONTROL WITH COMBINED SYSTEM IDENTIFICATION AND PID CONTROLLER TUNING

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Abstract: In this paper we propose a systematic methodology that integrates the three main phases of the design of an industrial control system, namely, the identification phase, the tuning of the (PID) feedback controller and the design of a (noncausal) open-loop action. In particular, a first-order-plus-dead-time model of the process is estimated after having filtered properly the data collected in the identification experiment. Then, the tuning of the controller is based on frequency loop shaping where the target closed-loop system bandwidth is selected by considering the desired output transition time from one set-point value to another. Finally, the noncausal open-loop command input is synthesised by applying a stable input-output inversion procedure. Simulation results show the effectiveness of the methodology.

Keywords: Noncausal feedforward control, PID control, identification for control.

1. INTRODUCTION

It is known that Proportional-Integral-Derivative (PID) controllers are the most adopted controllers in industrial settings, because they are capable to provide a satisfactory performance for a wide range of processes despite their simplicity. Actually, many tuning rules have been devised in the last sixty years in order to make their application easier (O'Dwyer, 2006). These tuning rules are usually based on the assumption that a first-order-plus-dead-time (FOPDT) model of the process is available. Different techniques have been proposed for estimating a FOPDT model of the process based on a simple (open-loop or closed-loop) experiment. Each of them has its pros and cons (Visioli, 2006) and therefore the chosen procedure plays a major role in the overall control system design, but in spite of this, the identification phase is usually not related to the selected tuning rule (Leva, 2005). A notable exception in this context is the methodology proposed in (Grassi *et al.*, 2001), where a frequency loop-shaping approach is exploited.

From another point of view, it is also recognized that the performance of a PID control loop is determined also by the suitable implementation of those functionalities that have to (or can) be added to the basic PID control law in order to deal with practical issues (Visioli, 2006). In this context a particular attention has been paid by researchers to the synthesis of a suitable open-loop control action in order to improve the set-point following performance (see, for example, (Wallen and Åström, 2002; Visioli, 2004)). In particular, a noncausal approach has been proposed in (Piazzi and Visioli, 2006). It consists in applying a suitable command signal to the closed-loop control system in order to achieve a desired transient response when the process output is required to assume a new value. This command signal is determined by means of a stable input-output inversion procedure for which a closed-form solution has been determined. Being an open-loop approach, the inversion technique obviously relies heavily on the accuracy of the estimated process model. Although it has been shown that the noncausal approach is effective with different identification procedures and different values of the PID parameters, in the current literature the open-loop control design is independent from the identification strategy and from the tuning of the PID controller.

Thus, in this paper we present a methodology that integrates coherently the identification technique, the design of the PID feedback controller and the design of the noncausal open-loop control action. In particular, after having selected a desired output transition time from a set-point value to another, a standard prediction error/maximum likelihood method is applied to suitably filtered input/output data collected by applying a generalized binary noise (GBN) signal to the process, in order to estimate a FOPDT model of the (self-regulating) process. Then, the PID controller parameters are determined by frequency loop shaping, where the target loop shape is determined in order to achieve the desired bandwidth of the system and, at the same time, in order to minimise the effect of the uncertainties in the bandwidth where the command signal to be applied to the closed-loop system has its main frequency content. Thus, the effectiveness of its application is increased (Devasia, 2002).

2. METHODOLOGY

2.1 Control scheme

We consider the unity-feedback control loop shown in Figure 1, where the "true" process $P(s)$ to be controlled (assumed to be self-regulating) is modelled as a FOPDT transfer function, i.e.:

$$\tilde{P}(s) = \frac{K}{Ts+1}e^{-\theta s}. \quad (1)$$

This is a typical choice in industrial practice, since this model can describe well the dynamics of many industrial processes. Further, a FOPDT model allows to exploit an analytical solution of the stable input-output inversion procedure (Piazzi and Visioli, 2006) (see Section 2.4).

The (output-filtered) PID feedback controller transfer function is denoted as follows:

$$C(s) = K_p\left(1 + \frac{1}{T_i s} + T_d s\right)\frac{1}{T_f s+1} \quad (2)$$

where K_p is the proportional gain, T_i is the integral time constant, T_d is the derivative time constant and T_f is the time constant of a first- order filter that makes the transfer function proper. The value of T_f can be selected, once the other parameters are determined, such that the filter

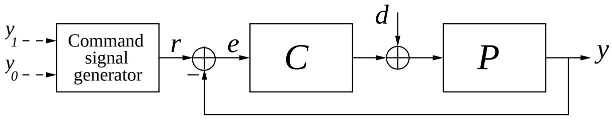

Fig. 1. The considered control scheme.

dynamics does not influence the dynamics of the PID controller and the effects of the measurement noise are reduced as much as possible.

The signal $r(t)$, to be applied to the closed-loop system when a process output transition from a previous value y_0 to a new value y_1, to be performed in a given transition time τ, is required, is determined by a command signal generator that implements a stable input-output inversion procedure. In the following, without loss of generality, we assume $y_0 = 0$.

2.2 Identification

A large number of different identification procedures have proposed in the literature and applied successfully in practical cases (Ljung, 1999). As it will be clarified in the following sections, for the purpose of the methodology proposed in this paper, it is necessary to estimate the FOPDT model parameters that minimises the process model uncertainty in a certain (user defined) frequency range $[0, 2\omega_c]$, where the choice of w_c will be discussed in Section 2.5. However, it is worth stressing at this point that while w_c is the desired bandwidth of the closed-loop system, the range $[0, 2\omega_c]$ is motivated by the optimisation problem that is solved for the tuning of the PID controller (see Section 2.3). In any case, it is well-known that the selection of a good test signal plays a key role in the identification. Actually, two aspects are important in selecting the input signal for process control: the signal-to-noise ratio and the power spectrum. To obtain high value of signal-to-noise ratio the use of signals with as much signal power as possible is necessary. Unfortunately, this leads in general to very high signal amplitude that can excite the nonlinearity of the system. Moreover, the signal amplitude is obviously constrained by the physical limitations of the actuators. For these reasons, for a given power, the signal with smallest amplitude is desirable. One of the index used to identify the best signal with respect to this property is the crest factor C_r (Guillaume *et al.*, 1991), defined as:

$$C_r := \frac{\max_n u(n)}{\sqrt{\sum_{n=1}^{N} u(n)^2}} \quad (3)$$

where N is the number of samples of the test signal. The crest factor provides a measure of how well distributed the signal values are over the input span. A good test signal must have a small crest factor; in fact, this indicates that most of the elements in the sequence are close to the minimum or to the maximum value of the series. For this reason, the binary signals ($C_r = 1$) are normally used. A GBN signal $u(t)$ assumes two values, namely, $-a$ and $+a$, which have to be selected, as already mentioned, in order to achieve the maximum amplitude of the signal without exciting the nonlinear dynamics. At each candidate switching time t, the amplitude may switch according to the following rule:

$$\begin{array}{c} P[u(t) = -u(t-1)] = psw \\ P[u(t) = u(t-1)] = 1 - psw \end{array} \qquad (4)$$

where psw is the switching probability, which is determined by:

$$psw = \frac{T_{min}}{ET_{sw}} \qquad (5)$$

where T_{min} is the minimum switching time (in samples) and ET_{sw} is the mean switching time. The selection of the parameters psw and ET_{sw} could have a deep impact on the identification results. In this work, the minimum switching time T_{min} is set to 1 (sample), while the mean switching time ET_{sw} is defined on the basis of the step response of the system, as suggested in (Zhu, 2001):

$$ET_{sw} = \frac{T_s}{3} \qquad (6)$$

where T_s is the 2% open-loop step response settling time.
The duration of the identification experiment has been defined as $20T_s$ (Zhu, 2001). The advantage of this kind of signal is that its spectrum do not present dips (unlike Pseudo Random Binary Signals) and has flexible length, allowing a simple conversion of its duration from samples to time units.
Once the input/output data are collected, a prediction error method, based on the minimization of the squared identification errors (Ljung, 1999) is applied in order to estimate the parameters of the FOPDT model $P(s)$. In order to minimise the resulting modelling uncertainty in the specific frequency range $[0, 2\omega_c]$, a data filtering preprocessing technique has to be used. This procedure consists in the application of a fifth-order Butterworth lowpass filter with $2\omega_c$ as the cutoff frequency.

2.3 PID controller tuning

The tuning of the PID controller is performed in order to achieve a closed-loop bandwidth ω_c and in order to minimise the sensitivity function (i.e. to minimise the effect of the plant uncertainties) in the frequency range $[0, \omega_c]$, namely the frequency range spanned by the employed command signal (see Section 2.4). This can be met by applying a frequency loop shaping technique where the target loop shape $\bar{L}(s)$ is selected as (Grassi *et al.*, 2001)

$$\bar{L}(s) = \frac{\omega_c}{s} e^{-\theta s}. \qquad (7)$$

Thus, once the target loop shape is defined, the PID parameters can be determined so that the open-loop transfer function is as much as close to $L(j\omega)$ in an $\mathcal{L}_\infty$ sense, namely, by solving the following optimization problem:

$$\min_{K_p, T_i, T_d} \|C(j\omega)\tilde{P}(j\omega) - \bar{L}(j\omega)\|_\infty, \quad \omega \in [\omega_c/10, 2\omega_c]. \qquad (8)$$

In this context, the choice of the frequency range $[\omega_c/10, 2\omega_c]$ (which yields to the value of the cutoff frequency of the Butterworth filter employed in the identification procedure) is motivated by obtaining a good approximation around the gain crossover frequency ω_c. It is worth noting that the PID controller expression can be appropriately rewritten so that the objective function is convex (affine) in the design parameters (Grassi *et al.*, 2001). The optimization problem can be therefore solved by applying any standard optimization technique.

2.4 Determination of the command input signal

Once the feedback PID controller has been tuned, the noncausal open-loop control action $r(t)$ can be determined by applying a stable input-output inversion procedure (Piazzi and Visioli, 2006). Roughly speaking, the procedure consists in finding the bounded closed-loop command function $r(t)$ that causes a desired output function $y_d(t)$.
In particular, as a desired output function that defines the transition of the process variable from a set-point value $y_0 = 0$ to another y_1 (to be performed in the time interval $[0, \tau]$) a third-order "transition" polynomial (Piazzi and Visioli, 2001) can be selected, namely, a polynomial function that satisfies boundary conditions and that is parameterised by the transition time τ:

$$y_d(t;\tau) = y_1 \left(-\frac{2}{\tau^3} t^3 + \frac{3}{\tau^2} t^2 \right). \qquad (9)$$

Outside the interval $[0, \tau]$ the function $y_d(t;\tau)$ is equal to 0 for $t < 0$ and equal to y_1 for $t > \tau$. It is worth stressing that expression (9) represents a monotonic function with neither undershooting nor overshooting and its use is therefore very appealing in the context of process control. Further, it guarantees that a continuous command input function results.
The closed-form expression of the command input $r(t; K, T, \theta, K_p, T_i, T_d, T_f, \tau)$, defined over the interval $(-\infty, +\infty)$, that causes the desired output $y_d(t;\tau)$, can be then determined by applying to the nominal closed-loop system the stable input-output inversion procedure presented in (Piazzi and Visioli, 2006) (note that a second-order Padé approximation is employed to obtain a closed-loop rational transfer function). Actually, from a practical point of view, since the synthesized function is defined over the interval $(-\infty, +\infty)$, it

is necessary to adopt a truncated function $r_a(t;\tau)$, resulting therefore in an approximate generation of the desired output $y_d(t;\tau)$. In particular, a preactuation time t_s and a postactuation time t_f can be selected so that $r_a(t;\tau) = 0$ for $t < t_s$ and $r_a(t;\tau) = y_1$ for $t > t_p$. By taking into account that the preactuation and postactuation inputs (i.e. the input defined for $t < 0$ and $t > \tau$ respectively) converge exponentially to zero at time $t \to -\infty$ and to y_1 at time $t \to +\infty$, an arbitrarily precise approximation can be accomplished (Piazzi and Visioli, 2005). Practically, the method suggested in (Perez and Devasia, 2003) can be adopted. It consists of selecting

$$t_s = -\frac{10}{D_{rhp}} \qquad t_p = \frac{10}{D_{lhp}} \tag{10}$$

where D_{rhp} and D_{lhp} are the minimum distance of the right and left half plane zeros of the closed-loop system, respectively, from the imaginary axis of the complex plane.

2.5 Bandwidth selection

The selection of the closed-loop bandwidth ω_c is a direct consequence of the required transition time τ. Actually, if we consider that the desired open-loop transfer function $\bar{L}(s)$ is achieved, we have that, for different values of θ, the determined command signal has almost all its frequency content in the range $[0, \omega_c]$ by selecting

$$\omega_c = \frac{5}{\tau}. \tag{11}$$

In particular, if we consider the normalised power spectrum of the determined command input, we have that, with expression (11), frequencies higher than ω_c have an amplitude of less than 10% with respect to the amplitude of the frequency $\omega = 0$. Details are omitted for brevity, however, this can be ascertained easily by exploiting the analytical closed-form expression of the command input.

It is worth noting at this point that the method is applicable if the dead time is not too large so that the asimptotic stability of the system is ensured. In other words it has to be at least

$$\theta < \frac{\pi}{2\omega_c}. \tag{12}$$

If this condition is not met, then the desired transition time τ has to be increased.

2.6 Procedure

The devised overall design procedure can be summarised as follows:

(1) Define the new set-point value y_1 and the transition time τ.
(2) Set $\omega_c = 5/\tau$.
(3) Perform the identification experiment with a GBN signal and collect the input-output data.
(4) Filter the collected data with a fifth-order Butterworth lowpass filter with $2\omega_c$ as the cutoff frequency.
(5) Apply a prediction error method in order to estimate a FOPDT transfer function.
(6) Solve the optimisation problem (8) in order to find the PID parameters.
(7) Determine the closed-loop command function $r(t)$ by applying a stable inversion procedure.
(8) Apply the determined command input function to achieve the desired output transition.

3. SIMULATION RESULTS

3.1 Example 1

In order to illustrate the overall methodology, the following (high-order) process is simulated:

$$P(s) = \frac{10}{(s+1)^3(3s+1)} e^{-2s}. \tag{13}$$

The control requirement is to perform a set-point transition from $y_0 = 0$ to $y_1 = 1$ in a time interval $\tau = 25$. Thus, we have $\omega_c = 0.2$. We selected $a = 1$ for the generation of the GBN signal to be employed for identification purpose. The process output measurement has been corrupted with white noise whose power is 0.05. The resulting input/output data are plotted in Figures 2. By applying the prediction error/maximum likelihood method, after having filtered appropriately the data, the estimated FOPDT model results to be

$$\tilde{P}(s) = \frac{10.06}{3.70s + 1} e^{-4.43s}. \tag{14}$$

The solution of the optimisation problem (8) yields the following PID parameters value: $K_p = 0.078$, $T_i = 3.92$, $T_d = 0.22$. Then, $T_f = 0.01$ has been selected. The Bode plot of the resulting open-loop system $C(s)\tilde{P}(s)$ and of the target function $\bar{L}(s)$ are shown in Figure 3. The resulting command input function is shown in Figure 4. The corresponding process output, together with the obtained control variable is shown in Figure 5 where results obtained with the application of a step input are also shown for comparison. Note that, despite the high-order dynamics of the process and the significant dead time, the output transition time obtained by applying the inversion-based command input is almost equal to the desired one $\tau = 25$. Actually, the presence of a time delay in the closed-loop response when the noncausal approach is employed is due to the presence of the preactuation time interval. Further, the PID tuning is satisfactory as the oscillatory set-point step response is avoided by implementing the inversion-based procedure.

The effectiveness of the approach is confirmed if we decrease the transition time to $\tau = 17$. In this case we have $\omega_c = 0.3$, $K_p = 0.12$, $T_i = 4.2$, $T_d =$

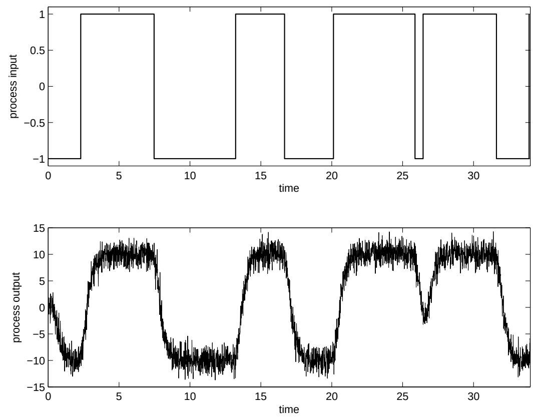

Fig. 2. Input and output data employed for identification in the simulation example 1 ($\tau = 25$).

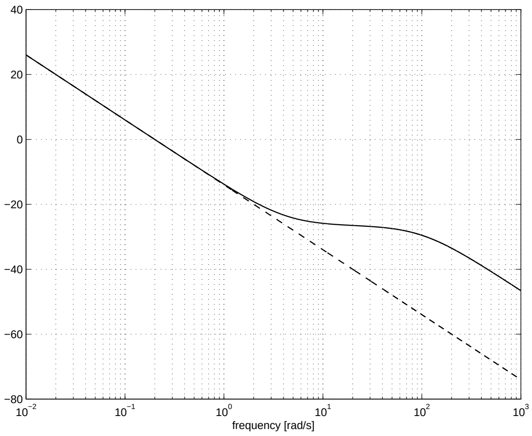

Fig. 3. Bode plot of the resulting open-loop system $C(s)P(s)$ (solid line) and of the target function $\bar{L}(s)$ (dashed line) for the simulation example 1 ($\tau = 25$).

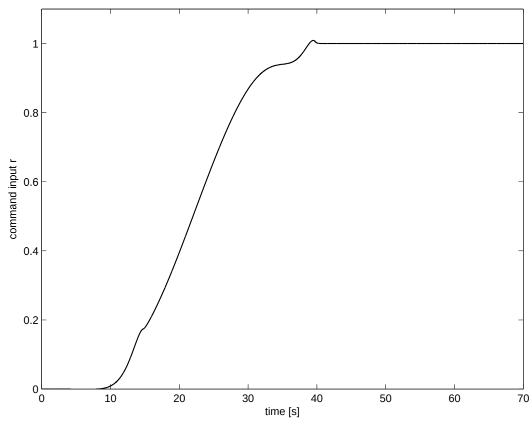

Fig. 4. Command input function r for the simulation example 1 ($\tau = 25$).

0.45. The resulting command input and process output (together with the control variable) are shown in Figures 6 and 7 respectively. Also in this case the performance obtained is compared with the response to a set-point step signal. It appears that the transition time obtained is very close to

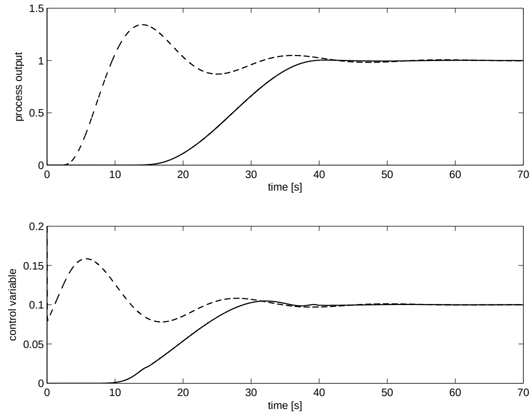

Fig. 5. Process output and control variable with the determined command input (solid line) and with a step set-point signal (dashed line) for the simulation example 1 ($\tau = 25$).

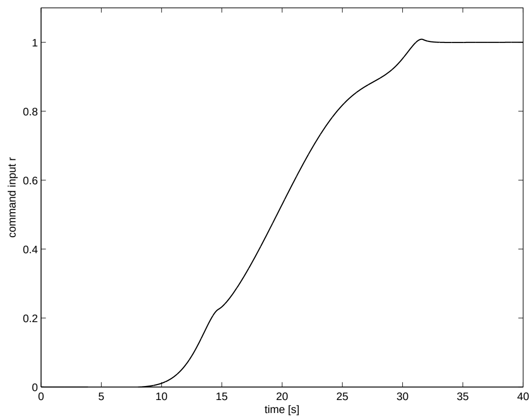

Fig. 6. Command input function r for the simulation example 1 ($\tau = 17$).

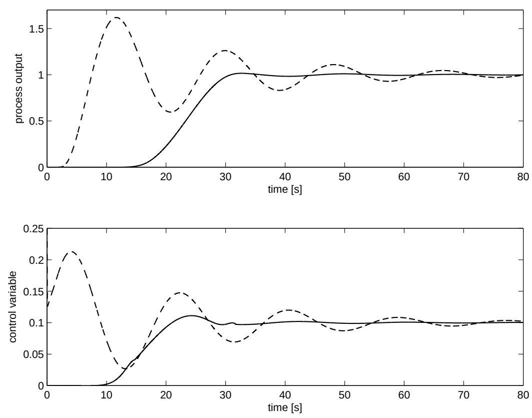

Fig. 7. Process output and control variable with the determined command input (solid line) and with a step set-point signal (dashed line) for the simulation example 1 ($\tau = 17$).

the desired one $\tau = 17$ despite the aggressive tuning of the controller.

3.2 Example 2

As a second example, consider the process:

$$P(s) = \frac{1}{(s+1)^8}. \qquad (15)$$

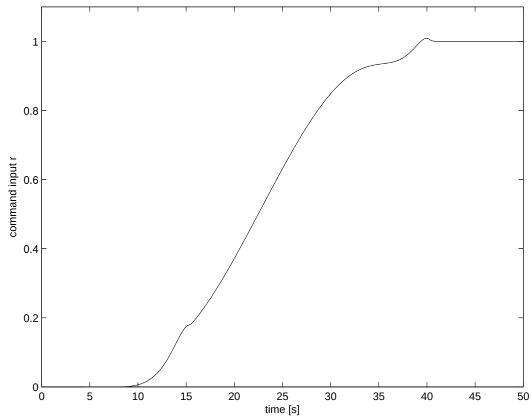

Fig. 8. Command input function r for the simulation example 2 ($\tau = 25$).

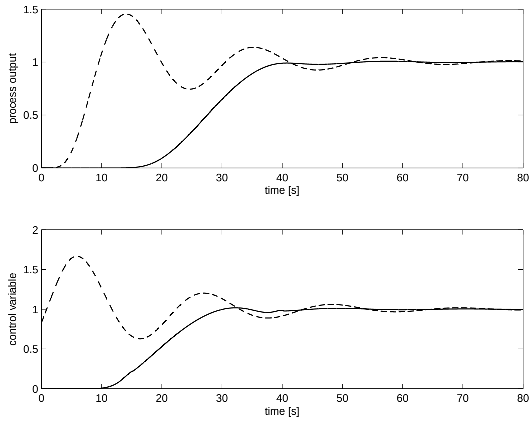

Fig. 9. Process output and control variable with the determined command input (solid line) and with a step set-point signal (dashed line) for the simulation example 2 ($\tau = 25$).

The control requirement is again to perform a set-point transition from 0 to $y_1 = 1$ in a time interval $\tau = 25$. Thus, we have $\omega_c = 0.2$. The same value $a = 1$ for the generation of the GBN signal has been employed for identification purpose (note that, as in the previous case, the process output measurement has been corrupted with white noise whose power is 0.05). The estimated FOPDT model results to be

$$\tilde{P}(s) = \frac{1.01}{3.96s + 1} e^{-4.58s}. \qquad (16)$$

The solution of the optimisation problem (8) yields the following PID parameters value: $K_p = 0.83$, $T_i = 4.19$, $T_d = 0.23$ ($T_f = 0.01$). The resulting command input function is shown in Figure 8. The corresponding process output and the control variable are shown in Figure 9 where results obtained with the application of a step input are also shown for comparison. Note that also in this case, despite the different tuning of the PID controller, the output transition time obtained by applying the inversion-based command input is almost equal to the desired one $\tau = 25$.

4. CONCLUSIONS

In this paper a methodology that integrates the identification technique, the feedback PID controller tuning and the (noncausal) open-loop action has been proposed. It allows to achieve a process output transition in a desired transition time. Simulation results have shown the effectiveness of the technique which can be automated easily and appears therefore suitable to apply in industrial settings.

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