Simultaneous Control Loop Performance Assessment and Process Identification Based on Fractional Models

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Abstract: Control loop performance assessment procedures are established as key cornerstone of process optimization and monitoring. Unfortunately, many methods do not consider the maximum possible performance which can be achieved by the fixed structure controller installed in the loop (typically PID). In authors’ recent work such method was described. It was shown that – with respect to classical minimum variance method – the maximum performance is strongly influenced by the process normalized dead time. Consequently, the process model should be re-estimated during the plant operation. This paper describes technique which integrates continuous estimation of process model including normalized dead-time and control loop performance assessment. The process model is considered as fractional in order to fit well to distributed parameter systems appearing in chemical process control industries. All procedures are packed into advanced function blocks which are ready for real-time applications.

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1. INTRODUCTION

In last decades, industry is facing a strong pressure for plant and machine optimization in order to achieve energy and material savings and increase product quality. Control loop performance assessment (CLPA) can be viewed as one of relevant technologies to handle this issue. Since 1970, it became an inseparable part of widely distributed control systems – especially in refineries, oil and chemical sectors. The control engineers proved that correct CLPA application leads to huge energy and material savings and increased overall product quality (Desborough and Miller (2002)). Therefore, CLPA faces growing interest in both research and engineering community. Several surveys of existing CLPA approaches have been done e.g. in Harris et al. (1999); Aström and Hägglund (2006); Shardt et al. (2012); Jelali (2013).

Unfortunately, the utilization of CLPA is still undervalued despite its evident positive impact. Analysis of current state clearly shows, that there is a need for hard work at both research and engineering side. The controllers are frequently tuned only once, the others work with default parameters or just in manual mode. Even when the controllers are initially well tuned they should be continuously monitored because process dynamics varies and the actuators – namely valves – degrade over the time. Several renowned studies declare that about 70% of control loops are not properly tuned also due to the lack of monitoring tools based on exact problem formulation.

It is worth to mention that large-scale process industries often work with stand-alone monitoring system which analysis off-line data gained from a signal database. Commonly, the current control quality is compared to the best linear controller (minimum variance – see e.g. Lynch and Dumont (1996); Harris et al. (1999)).

Today, those traditional concepts need substantial revision. More specifically, the tighter collaboration with process controllers should be formed to make CLPA methods most effective and reliable. Firstly, one needs an insight what is the best performance achievable by the controller currently integrated in the loop which has typically fixed structure – PI or PID. This challenge was addressed earlier e.g. in Qin (1998); Ko and Edgar (1998); Grimble (2003); Thyagarajan et al. (2003). However, only the low order plant models are used there and the maximum achievable performance is computed numerically. The more pragmatic approach can be examined in Huang (2003) where a trade-off curve between input and output variance is taken into account. Secondly, at least a rough knowledge of the process model is necessary for more accurate estimation of maximum achievable performance. It was shown e.g. in Harris et al. (1999) that the performance index depends ...
significantly on the process dead time. Taking into account that the process dynamics varies over the time, the process model should be evidently re-estimated during the plant operation. It will help to make more precise performance evaluation and minimize the number of fake alarms. Consequently, the plant operators will concentrate on the most problematic loops. Moreover, the methods estimating both the process model and actual performance index need to be minimally invasive and should work in the closed loop. A majority of recent research concentrates only on closed loop identification from a setpoint step test, see e.g. Okamoto et al. (1996); Liu and Furong (2009); Cai et al. (2004). For practical applications, techniques dealing with more general input-output data are necessary.

One perspective approach is documented in this paper. It is a priori assumed that the process can be described by multiple fractional-pole model. In contrast to other methods, only a few characteristic numbers are estimated. Clearly, the model estimation can be done when the plant dynamics is sufficiently excited. In practice, it happens when the process changes its operating point or if some disturbance affects the loop. If the system is not excited for a long time a low-amplitude harmonic signal is injected to the loop. In this case, also the control loop performance index can be estimated simultaneously.

The rest of the paper is organized as follows: In Section 2, the problem of performance index estimation is formulated. Section 3 describes possible model estimation technique and discuss its advantages and drawbacks. Illustrative examples are shown in Section 4. Concluding remarks and ideas for further work are given in Section 5.

2. PROBLEM FORMULATION

2.1 Multiple fractional pole model

As proposed in Charef et al. (1992), to cover the huge number of essentially monotone real processes (Åström and Hågglund (2004)), one has a priori to consider the multiple fractional pole model in the form

$$P(s) = \frac{K}{\prod_{i=1}^{p}(\tau_is + 1)^{n_i}},$$

where \( p \) is arbitrary integer number and \( K, \tau_i, n_i \) \( i = 1, 2, \ldots, p \) are positive real numbers.

Remark 1. If all \( n_i, \quad i = 1, 2, \ldots, p \) are integer numbers, one obtains a classical integer-order transfer function in a Bode’s form.

Remark 2. If \( p \to \infty \) then the set of all transfer functions (1) contains also processes with dead time and approximates several processes with transcendent transfer functions (e.g. heat transfer).

2.2 Characteristic numbers – experimental data

Three-parameter time domain process description is well accepted in the control community. The authors’ previous works vindicate the usage of first three moments \( m_i \) of the impulse response \( h(t) \) instead of numbers obtained from the step response using its tangent line in the inflexion point. The application of time moments in control field

$$\ln(|S(j\omega)|) \quad \ln(M_S)$$

$$\Omega_0 \quad \Omega_1 \quad \Omega_\infty$$

$$\omega_d \quad M_{\omega_d} \quad \text{reference } S_R(j\omega)$$

$$\text{optimal (well tuned) } S_D(j\omega) \quad \text{actual (poorly tuned) } S(j\omega)$$

![Fig. 1. Ideal (reference) and real shapes of sensitivity functions](image)

firstly appeared in Maamri and Trigeassou (1993). They are defined as

$$m_i = \int_0^\infty t^i h(t)dt, \quad i = 0, 1, 2$$

and may be converted to another more suitable group of numbers \( \{\kappa, \mu, \sigma^2\} \) (Schlegel and Večerek (2005)) defined as

$$\kappa = \int_0^\infty h(t)dt = m_0, \quad \mu = \int_0^\infty \frac{th(t)dt}{h(t)dt} = \frac{m_1}{m_0}, \quad \sigma^2 = \int_0^\infty \frac{(t-\mu)^2h(t)dt}{h(t)dt} = \frac{m_2}{m_0} - \frac{m_1^2}{m_0^2}$$

It can be proved (Čech (2008)) that for transfer function (1), it holds

$$\kappa = K, \quad \mu = \sum_{i=1}^p \tau_i n_i, \quad \sigma^2 = \sum_{i=1}^p \tau_i^2 n_i.$$ 

From a control point of view, \( \kappa \) is equal to process static gain and \( \mu \) represents the residual time constant. Without loss of generality, the process can be normalized in gain and time, thus \( \bar{\kappa} = 1 \) and \( \bar{\mu} = 1 \). The remaining parameter \( \bar{\sigma}^2 = \sigma^2 / \mu^2 \) then has a meaning similar to normalized dead time.

2.3 Performance index

In authors’ previous work Schlegel et al. (2014), the novel performance index was defined. It is based on Bode theorem and an assumption of process monotony and controller exhibiting integrating behavior at low frequencies (like PI/PID). Consequently, an ideal shape of sensitivity function was defined (see Fig. 1). It is parameterized by only two numbers: maximum sensitivity function value \( M_s \) and available loop bandwidth \( \Omega_\infty \).

Then the performance index enumerates the ratio of the ideal to actual sensitivity function at some frequency from interval \( \omega_d \in (0, \Omega_0) \) (see Fig. 1). It can be defined as

$$I_p = \frac{M_{\omega_d} \omega_d \ln(M_s)}{\Omega_1 |S(j\omega)|} = \frac{M_{\omega_d} \omega_d \ln(M_s) - M_s + 1}{\ln(M_s) \ln(2\pi \Omega_0)} \cdot \frac{1}{|S(j\omega)|}$$

where \( \Omega_1 = \ln(M_s)M_s - M_s + 1 \) and \( \Omega_0 = \Omega_1/M_s \).
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