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

Radek Škarda * **Martin Čech** ** **Miloš Schlegel** ***

* *University of West Bohemia – NTIS, Pilsen, Czech Republic (e-mail: skardar@ntis.zcu.cz).*
** *University of West Bohemia – NTIS, Pilsen, Czech Republic (e-mail: mcech@ntis.zcu.cz)*
*** *University of West Bohemia – NTIS, Pilsen, Czech Republic (e-mail: schlegel@ntis.zcu.cz)*

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.

Keywords: Control loop performance assessment, process control, fractional-order systems, loop bandwidth, Bode theorem, sensitivity function, Fourier transform

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 has been done e.g. in Harris et al. (1999); Åström 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

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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 Hägglund (2004)), one has *a priori* to consider the multiple fractional pole model in the form

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

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

Remark 1. If all n_i, $i = 1, 2, \ldots, p$ 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

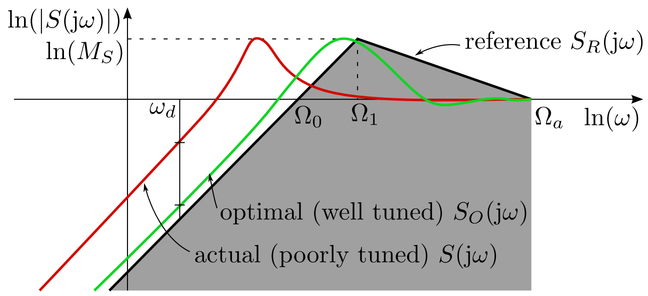

Fig. 1. Ideal (reference) and real shapes of sensitivity functions

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

$$m_i = \int_0^\infty t^i h(t)\mathrm{d}t, \qquad i = 0, 1, 2 \qquad (2)$$

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

$$\kappa = \int_0^\infty h(t)\mathrm{d}t = m_0, \qquad \mu = \frac{\int_0^\infty t h(t)\mathrm{d}t}{\int_0^\infty h(t)\mathrm{d}t} = \frac{m_1}{m_0},$$

$$\sigma^2 = \frac{\int_0^\infty (t-\mu)^2 h(t)\mathrm{d}t}{\int_0^\infty h(t)\mathrm{d}t} = \frac{m_2}{m_0} - \frac{m_1^2}{m_0^2}. \quad (3)$$

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

$$\kappa = K, \qquad \mu = \sum_{i=1}^{p} \tau_i n_i, \qquad \sigma^2 = \sum_{i=1}^{p} \tau_i^2 n_i. \qquad (4)$$

From a control point of view, κ is equal to process static gain and μ 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 monotonity 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 Ω_a.

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

$$I_p = \frac{M_s \omega_d}{\Omega_1 |S(j\omega_d)|} \doteq \frac{M_s \omega_d \ln(M_s)}{\Omega_a(\ln(M_s)M_s - M_s + 1)} \cdot \frac{1}{|S(\mathrm{j}\omega_d)|}, \qquad (5)$$

where $\Omega_1 \doteq \frac{\Omega_a(\ln(M_S)M_S - M_S + 1)}{\ln(M_S)}$ and $\Omega_0 = \Omega_1/M_S$.

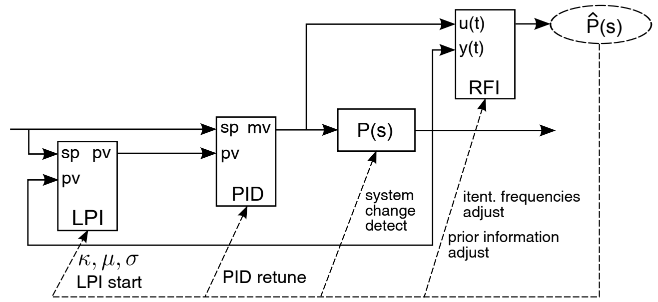

Fig. 2. Control loop performance assessment and system close-loop identification scheme

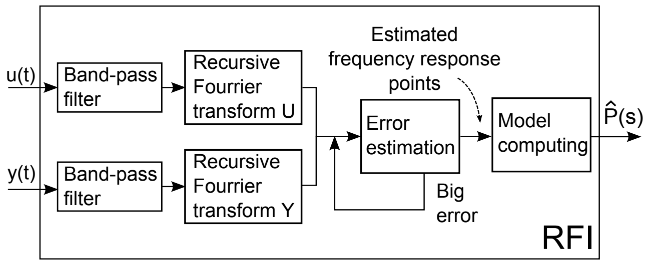

Fig. 3. General structure of RFI block with process frequency response estimator based on RDFT

Remark 1. The substantial advantage of index (5) is that it provides information whether the controller is too sluggish ($I_p \ll 1$) or too aggressive ($I_p \gg 1$), i.e. can handle to robustness/performance trade-off.

Recently, maximum achievable index $I_{pO}(\bar{\sigma}^2)$ was numerically evaluated depending on $\bar{\sigma}^2$ for PI/PID controller and process (1), see (Schlegel et al. (2014)). The consequent effort was devoted to development and testing of methods for real-time simultaneous estimation of both the process model (RFI) and loop performance index (LPI). The results are documented in upcoming sections.

In another authors' previous work Schlegel et al. (2013), the new algorithm for closed loop frequency domain estimation was introduced. The novel contribution of this work is the algorithm for computing time-domain model from estimated frequency response points. Moreover, the synergic fusion of loop performance index and closed-loop identification will be shown, see Fig. 2.

3. MODEL ESTIMATION

Closed-loop frequency domain estimation introduced in Schlegel et al. (2013) is called recursive frequency identification (RFI) and needs only minimum amount of *a priori* information about the process and it is capable to estimate several points of frequency response without need of external perturbations (due to advanced error estimation algorithm), see Fig. 3. Firstly, input signals have to be filtered by band-pass filters. Band-pass filter (BPF) eliminates both low-frequency bias terms and high-frequency noise and emphasizes the dynamics at frequency ω Åström and Hägglund (2006). Then running discrete Fourier transform (RDFT) algorithm is used to estimate frequency response function:

$$P(\mathrm{j}\omega) = \frac{Y(\mathrm{j}\omega)}{U(\mathrm{j}\omega)}.$$

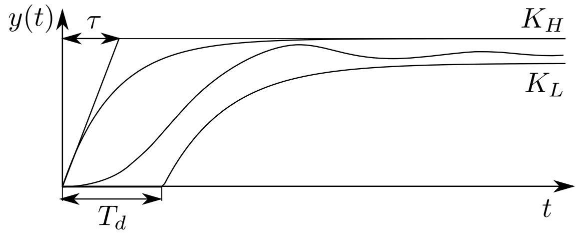

Fig. 4. *A priori* process knowledge for evaluation of error in computing process frequency response samples: residual time constant τ, maximum delay T_d, static gain limits K_L, K_H

Real and imaginary part of frequency response $P(\mathrm{j}\omega)$ can be computed as

$$\begin{aligned} \mathrm{Re}(P(\mathrm{j}\omega)) &= (\mathrm{Re}(Y)\mathrm{Re}(U) + \mathrm{Im}(Y) * \mathrm{Im}(U)) - E^2(U), \\ \mathrm{Im}(P(\mathrm{j}\omega)) &= (\mathrm{Im}(Y)\mathrm{Re}(U) - \mathrm{Re}(Y) * \mathrm{Im}(U)) - E^2(U), \end{aligned} \tag{6}$$

where $\mathrm{Re}(U)$, $\mathrm{Re}(Y)$, $\mathrm{Im}(U)$ and $\mathrm{Im}(Y)$ and $E^2(U)$ are computed by RDFT algorithm. In this algorithm the estimation error is used to decide whether the results are valid and could be sent to output of the block. Estimation error algorithm uses the *a priori* known bounds of the controlled system step response shown in Fig. 4. Prediction error is described by equations

$$\begin{aligned} Y(z) &= \sum_{k=0}^{M-1} y_k z^{-k} = \\ &= \left(\sum_{i=0}^{N-1} h_i z^{-i}\right)\left(\sum_{k=0}^{M-1} u_k z^{-k}\right) + R_0(z) - L_0(z) \\ Y(z) &= P(z) \cdot U(z) + R_0(z) - L_0(z) \\ R_0(z) &= \sum_{k=1}^{N-1}\left(\sum_{i=1}^{N-1} h_i u_{k-i-1}\right) z^{-k+1} \\ L_0(z) &= \sum_{k=1}^{N-1}\left(\sum_{i=1}^{N-1} h_i u_{M-i}\right) z^{-(M+k-1)} \\ |E(z)| &= |R_0(z) - L_0(z)| \le |R_0(z)| + |L_0(z)|, \end{aligned} \tag{7}$$

where h_i are impulse series coefficients, N is its length, M is RDFT buffer size. Remind, that suitable input signal is essential in any identification procedure. Here, the system has to be sufficiently excited on frequencies at which frequency response will be estimated. Easier way is to use special input signal in open loop but this type of experiment is not acceptable in most of practical cases. It is assumed that the process dynamic is estimated during step changes of working points or when performance index is estimated (both in closed loop).

From estimated frequency response points system model can be computed:

$$P(s) = K\frac{\mathrm{e}^{-Ds}}{(\tau s + 1)^n},\ K, D, \tau, n \in \mathbb{R}^+, \tag{8}$$

where K is process gain, D time delay, τ time constant and n model order (can be fractional). Process characteristic number for (8) can be computed:

$$\kappa = K, \qquad \mu = \tau n + D, \qquad \sigma^2 = \tau^2 n, \qquad \bar{\sigma}^2 = \frac{\sigma^2}{\mu^2}.$$

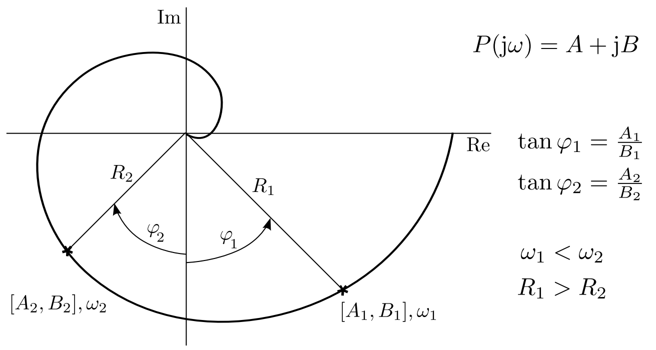

Fig. 5. System transfer function computation from two points of frequency response

For model (8) estimation, two points of system frequency response have to be known, see Fig. 5. From (8) we get

$$|P(j\omega)| = K\frac{1}{|(\tau j\omega + 1)^n|} = K(\tau^2\omega^2 + 1)^{-\frac{n}{2}} = R. \quad (9)$$

With two measured frequency response points $P(j\omega_1) = A_1 + jB_1,\ P(j\omega_2) = A_2 + jB_2$ ve get from (8) and (9)

$$\ln K - \frac{n}{2}\ln(\tau^2\omega_1^2 + 1) = \ln R_1, \quad (10)$$

$$\ln K - \frac{n}{2}\ln(\tau^2\omega_2^2 + 1) = \ln R_2 \quad (11)$$

and (assuming frequency response points are in 3rd and 4th quadrant)

$$-\frac{\pi}{2} - \arctan\frac{A_1}{B_1} = -\omega_1 D - n\arctan(\tau\omega_1), \quad (12)$$

$$-\frac{\pi}{2} - \arctan\frac{A_2}{B_2} = -\omega_2 D - n\arctan(\tau\omega_2). \quad (13)$$

After multiplying (12) and (13) by ω_2 and ω_1, respectively and substraction (13) from (12) we get

$$(\omega_1 - \omega_2)\frac{\pi}{2} + \omega_1\arctan\frac{A_2}{B_2} - \omega_2\arctan\frac{A_1}{B_1} = \\ = n\left[\omega_1\arctan(\tau\omega_2) - \omega_2\arctan(\tau\omega_1)\right]. \quad (14)$$

From equation (14) we get

$$L(\tau) = Q, \quad (15)$$

where

$$L(\tau) \triangleq \frac{\omega_2\arctan(\tau\omega_1) - \omega_1\arctan(\tau\omega_2)}{2\ln\frac{\tau^2\omega_2^2+1}{\tau^2\omega_1^2+1}} \quad (16)$$

and

$$Q \triangleq \frac{(\omega_2 - \omega_1)\frac{\pi}{2} + \omega_2\arctan\frac{A_1}{B_1} - \omega_1\arctan\frac{A_2}{B_2}}{2\ln\frac{R_1}{R_2}}. \quad (17)$$

Clearly, it holds:

$$\lim_{\tau\to 0} L(\tau) = 0, \quad \lim_{\tau\to\infty} L(\tau) = \frac{\pi(\omega_2 - \omega_1)}{4\ln\frac{\omega_1}{\omega_2}}. \quad (18)$$

Claim 1. Equation (15) has solution for $\tau > 0$ if and only if $Q \in \left\langle 0, \frac{\pi(\omega_2-\omega_1)}{4\ln\frac{\omega_1}{\omega_2}}\right)$. This solution is unique.

Equations for n, D and K can be derived:

After substraction (11) from (10) we get

$$\frac{n}{2}\left[\ln(\tau^2\omega_2^2 + 1) - \ln(\tau^2\omega_1^2 + 1)\right] = \ln\frac{R_1}{R_2}. \quad (19)$$

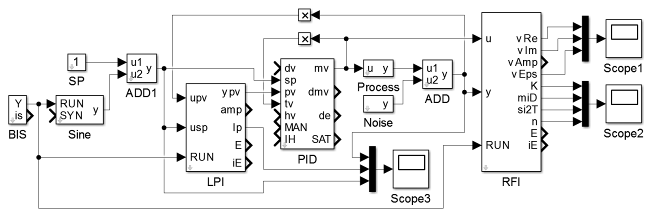

Fig. 6. Scheme of simultaneous loop performance index and frequency response points estimation algorithm

Theorem 1. $P(j\omega_1) = A_1 + jB_1 \ \wedge\ P(j\omega_2) = A_2 + jB_2$

$$\Updownarrow$$

$$\tau \text{ is solution of equation } L(\tau) = P, \quad (20)$$

$$n = \frac{2\ln\frac{R_1}{R_2}}{\ln\frac{\tau^2\omega_2^2+1}{\tau^2\omega_1^2+1}}, \quad (21)$$

$$D = \frac{1}{\omega_1}\left[\frac{\pi}{2}\arctan\frac{A_1}{B_1} - n\arctan\tau\omega_1\right], \quad (22)$$

$$K = R_1\left[\tau^2\omega_1^2 + 1\right]^{\frac{n}{2}}. \quad (23)$$

All parameters of model (8) will be positive if

$$Q \in \langle 0, \frac{\pi(\omega_2 - \omega_1)}{4\ln\frac{\omega_1}{\omega_2}}) \wedge \frac{\pi}{2}\arctan\frac{A_1}{B_1} - n\arctan\tau\omega_1 > 0$$

The proof follows immediately from (18) and from the fact the $L(\tau)$ is monotonously increasing function. □

Remark 2. Equations for n, D and K ((21), (22) and (23)) can be derived from (19), (12) and (10). Equation $L(\tau) = Q$ have to be solved numerically. In case the model order n is set by user, explicit relation for τ can be found.

4. ILLUSTRATIVE EXAMPLES

In both examples, the following procedure was used:

(1) Closed loop identification of two freq. response points by RFI block
(2) Freq. response points validation by error estimation algorithm
(3) Computation of process model (8)

Computations and simulations were made in Matlab/ Simulink, see Fig. 6, the process was considered as black box.

Example 1. The heat transfer in the metal rod is described by fractional order system $P_1(s) = \frac{1}{(0.17s+1)^{4.86}(0.385s+1)^{1.07}}$ and is being approximated by fractional-order transfer function (8). Model order $n \in \mathbb{R}$ is unknown, so τ has to be computed numerically, leading to $\hat{P}_1(s) = \frac{0.982e^{-0.0695s}}{(0.343s+1)^{1.194}}$ with characteristic numbers shown in Tab. 1. Results of this example – comparison of Nyquist and step response plots of nominal and identified system model are depicted in Fig. 7 and 8.

Example 2. Consider that simultaneous closed-loop identification and loop performance assessment is required. Harmonic perturbations used by control loop assessment algorithm are used for system identification. It can be useful in cases where setpoint changes in the system are rare. In this experiment (see scheme in Fig. 2), both loop performance index (5) and process model are obtained.

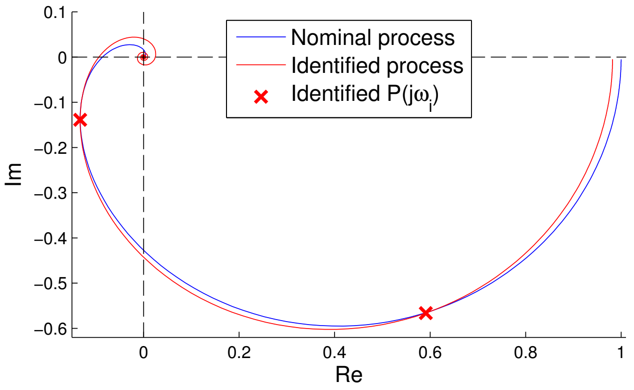

Fig. 7. Example 1 – Nyquist plots of nominal and identified process with estimated frequency response points

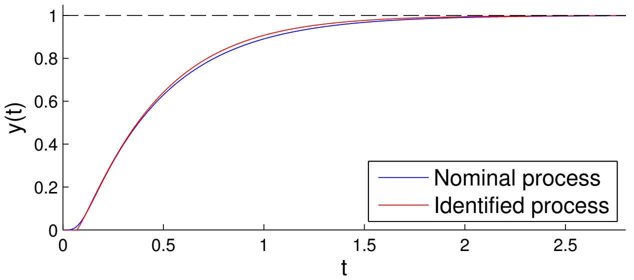

Fig. 8. Example 1 – Comparison of nominal and identified process step responses

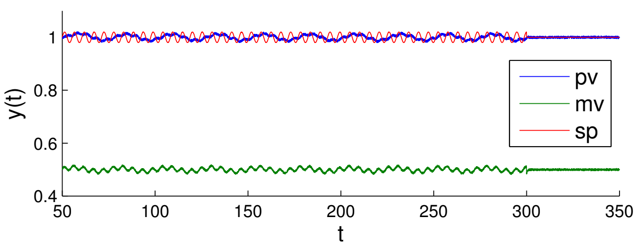

Fig. 9. Example 2 – Experiment progress

Further, it is shown that the process model can be used to performance index validity improvement and in the case of bad control quality for controller tuning. Model of second order system $P_2(s) = \frac{2e^{-0.2s}}{(1.5s+1)^2}$ in closed-loop experiment with PID controller was identified, see scheme in Fig. 6. Because external disturbances are supposed, the closed-loop system is perturbed on two frequencies with small amplitude. The first one is generated by LPI block (for performance index estimation) and the second one is added to setpoint, see Fig 9. In these specific conditions, the process model was identified by RFI block resulting to $\hat{P}_2(s) = \frac{1.99e^{-0.241s}}{(1.502s+1)^2}$, see Fig. 12, 10, 11 and Tab. 1. Simultaneously, the actual loop performance index was estimated as $I_{pA} = 0.224$ (see Fig. 13). For known $\bar{\sigma}^2$ it is possible to determine optimal performance index $I_{pO}(\bar{\sigma}^2) = 0.392$, see Fig. 14. Loop performance index can be computed as $\bar{I}_p = \frac{I_{pA}}{I_{pO}} = 0.571$. This value shows that performance of actual PID is not good and it should be retuned ($\bar{\sigma}^2$ could be used for obtaining new parameters), see Fig. 15.

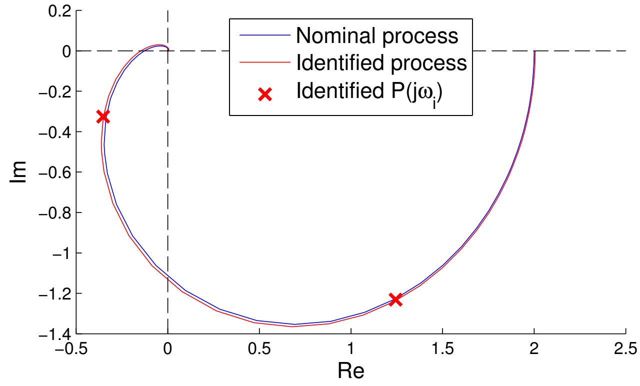

Fig. 10. Example 2 – Nyquist plots of nominal and identified process with estimated frequency response points

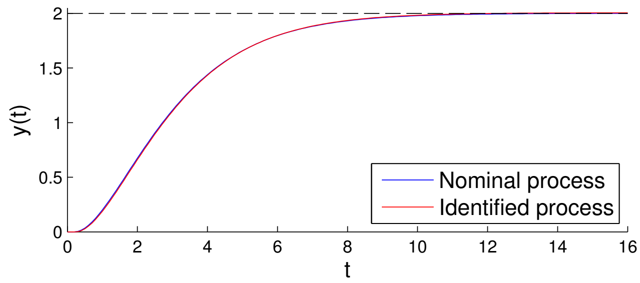

Fig. 11. Example 2 – Comparison of nominal and identified process step responses

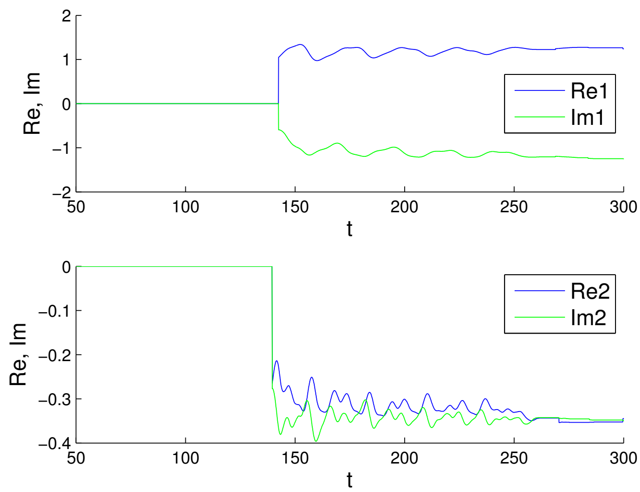

Fig. 12. Example 2 – Real and imaginary parts of frequency response points estimation

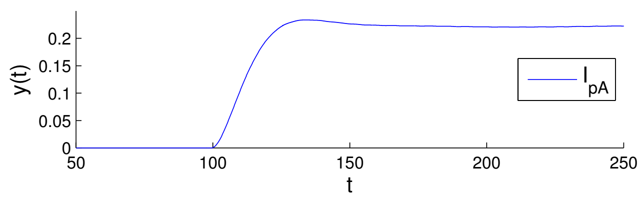

Fig. 13. Example 2 – Actual loop performance index I_{pA} estimation

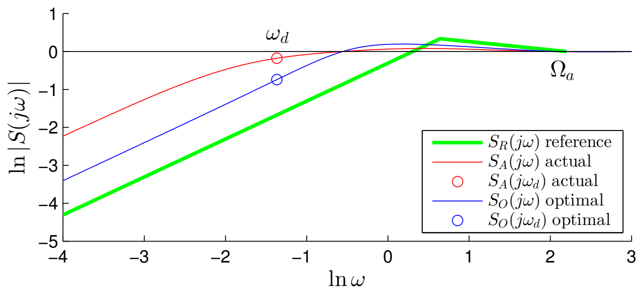

Fig. 14. Example 2 – Sensitivity functions comparison; $\Omega_a = 9\ rad \cdot s^{-1}$, $\omega_d = 2.55\ rad \cdot s^{-1}$, $A_d = 0.05$.

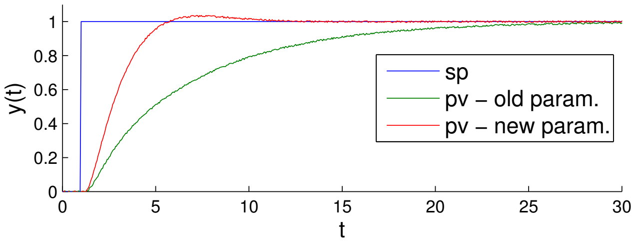

Fig. 15. Example 2 – Closed loop system step response

Example	κ	μ	σ^2	$\bar{\sigma}^2$	$\hat{\kappa}$	$\hat{\mu}$	$\hat{\sigma}^2$	$\hat{\bar{\sigma}}^2$
1	1	0.49	0.16	0.64	0.98	0.48	0.14	0.61
2	2	3.2	4.5	0.44	2.01	3.23	4.51	0.43

Table 1. Examples results – characteristic numbers of nominal and identified processes

5. CONCLUSION

In this paper a new approach to simultaneous control loop performance evaluation and process identification was described. It was assumed that the process is essentially monotone and can be described by multiple fractional pole model. It was shown that the process normalized dead-time can be estimated during working point transients or when the low-amplitude harmonic signal is injected into the loop. Simultaneously, the actual performance index can be estimated and compared to the maximum achievable one depending on actual normalized dead-time. For both tasks, running discrete Fourier transform was employed. All algorithms were implemented into Matlab/Simulink function blocks which are ready for real-time embedded devices.

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