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A MODEL BASED CONTROL PERFORMANCE ASSESSMENT APPLIED TO LABORATORY THERMAL PLANT

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ABSTRACT

Fast and efficient Control Performance Assessment (CPA) presented here was performed in three steps. Model $G_m(s)$, represent the dynamic of the process, such that the set-point and load disturbance responses of the evaluated controller in the loop with $G_m(s)$ and with the same controller in the loop with the process analyzed are in a very good agreement. The controller in the evaluated loop, with model $G_m(s)$, was retuned/redesigned by using the controller optimization design method based on the frequency response $G_m(i\omega)$ under constraints on the desired: sensitivity to measurement noise M_n, maximum sensitivity M_s and maximum complementary sensitivity M_p. Applying the unit load step disturbance, comparing the Integrated Absolute Error (IAE), the maximum deviation e_{max} of the controlled variable, the M_s, M_p and M_n obtained by the evaluated controller in the loop with $G_m(s)$, give us valuable information how far we are from an optimum solution and search new controller as the candidate for the calculation and implementation. Proposed method for CPA is illustrated by simulation of thermal plant model, with the band-limited white noise added to the controlled variable, and on a laboratory thermal plant with noise measurements.

INTRODUCTION

The main reason for poor control performance is, that the controllers are normally designed and tuned at the commissioning stage, but left unchanged after that for long period of time[1]. Basic idea of Control Performance Assessment (CPA), presented in earlier works, is to compare the actual variance of the controlled variable to the ideal one, followed by the detection of oscillatory and sluggish control loops. Oscillation in control loops due to valve hysteresis and friction are caused by the influence of nonlinearities [1,2,3,4].

The additional goal of CPA is to provide information on how poor performing control loops can be retuned/redesigned to obtain optimal performance, not only how well existing controllers are performing. Thus, defining optimal closed-loop performance is the starting point for the CPA method.

The optimal closed-loop performance is defined by the Integrated Absolute Error (IAE), following the load step, under constraints on the desired robustness. This method was proposed by Shinskey [5], and widely accepted in the PID controller optimization. In order to avoid large fluctuations of the control signal, additional requirement, taken into account is that the PID controller optimization must be performed under constraint on the desired sensitivity to measurement noise M_n. Optimal PID controller is defined with two robustness indices, maximum sensitivity M_s and maximum complementary sensitivity M_p, and by two performance indices, IAE and M_n.

EXPOSITION

In the CPA presented here, optimal closed-loop performance, is defined by the IAE obtained by the PID controller optimization under constraints on the desired values of M_n, M_s and M_p. For efficient application of the proposed CPA, authentic process dynamics characterization of a large class of stable, integrating and unstable processes, by the model $G_m(s)$, is required. That means if the model $G_m(s)$ is used, instead of the process $G_p(s)$, almost the same set-point and load disturbance step responses are obtained in the loop with the evaluated/proposed controller $C(s,q)$. The robustness and performance, as indices for control loops, must be the same if the model $G_m(s)$ is used, instead of the process $G_p(s)$, in the control loop with the evaluated/proposed controller $C(s,q)$, where q is the vector of the controller parameters.

The model $G_m(s)$, used in design and optimization procedure, is defined with quadruplet k_u, ω_u, φ, A [6]

$$G_m(s) = \frac{A\omega_u e^{-\tau s}/k_u}{s^2 + \omega_u^2 - A\omega_u e^{-\tau s}},$$

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$$A=\frac{\omega_u k_u G_p(0)}{1+k_u G_p(0)},\ \tau=\frac{\varphi}{\omega_u} \tag{1}$$

where k_u is the ultimate gain of the process $G_p(s)$ and φ is the angle of the tangent to the Nyquist curve $G_p(i\omega)$ at the ultimate frequency ω_u, as presented in Fig. 1

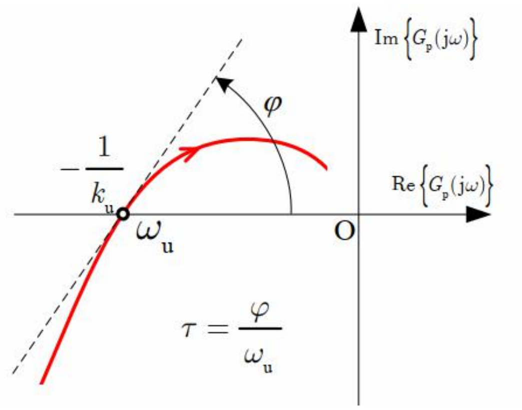

Fig. 1. Illustration of tangent rule

The PID controller $C(s,q)$, relating the controlled variable $Y(s)$ to the control variable $U(s)$, are defined here by parameters $q=\{k,k_1,k_d,T_f\}$ and the following implementation

$$U(s)=k\big(bR(s)-Y_f(s)\big)+\frac{k_i}{s}\big(R(s)-Y_f(s)\big)-k_d sY_f(s),$$

$$Y_f(s)=F(s)Y(s) \tag{2}$$

with $b=0$ if not stated otherwise. The lowpass filter $F(s)=F_n(s)$ is defined by the

$$F_n(s)=\frac{1}{(T_f s+1)^n},\ n=1,2 \tag{3}$$

The load step disturbance and the IAE are defined by

$$Y_d(s,q)=\frac{G_x(s)}{1+C(s,q)G_x(s)}\frac{1}{s},\ IAE(q)=\int_0^\infty |y_d(t,q)|dt. \tag{4}$$

In reality $G_x(s)=G_p(s)$, while in optimization $G_x(s)=G_m(s)$. The effect of the load step disturbance can be measured in the frequency domain by the following performance index

$$J_d(q)=\max_\omega |Y_d(i\omega,q)|. \tag{5}$$

Optimal values of the parameters q can be determined from $\min_q J_d(q)$ under constraints on the desired sensitivity to measurement noise M_{nd} and desired robustness M_{sd}, M_{pd}

$$M_{nz}\le M_{nzd},M_s\le M_{sd},M_p\le M_{pd} \tag{6}$$

where $M_{nz}=M_{n\infty}$. For the loop-transfer function defined by $C_L(s,q)$, and if the first-order noise filter is applied, parameters $M_{nz}=M_{n\infty}$, M_s, M_p are given by

$$C_L(i\omega,q)=C(i\omega,q)G_x(i\omega),\ S(i\omega,q)=\frac{1}{1+C_L(i\omega,q)};$$

$$C_u(i\omega,q)=C(i\omega,q)S(i\omega,q) \tag{7}$$

$$M_{n\infty}=\max_\omega |C_u(i\omega,q)|$$

$$M_s=\max_\omega |S(i\omega,q)|,\ M_p=\max_\omega |1-S(i\omega,q)| \tag{8}$$

Applying the penalty function technique, the controller optimization under constraints is transformed into

$$q=\arg\left\{\min_q\left(J_d(q)+\lambda_0\sum_1^3\psi_i(\chi_i-\chi_{id})\right)\right\} \tag{9}$$

$$\psi_i(\chi_i-\chi_{id})=\begin{cases}0 & for\ \chi_i\le\chi_{id}\\ \chi_i-\chi_{id} & for\ \chi_i>\chi_{id}\end{cases} \tag{10}$$

where $\lambda_0=10^{10}$, $\chi_1=M_s$, $\chi_{1d}=M_{sd}$; $\chi_2=M_p$, $\chi_{2d}=M_{pd}$, $\chi_3=M_{n\infty}$, $\chi_{3d}=M_{n\infty d}$.

Optimization (9)-(10) can be performed by using Particle Swarm Optimization (PSO) algorithm [7]. Parameters defined in [8, Appendix B] are applied as initial values $q_0=\{k_0,k_{i0},k_{d0},T_{f0}\}$ for optimization (7)-(8). PID_{tun} controller was defined by q_0.

For the PID controller, with first-order noise filter, $M_{n\infty}$ in (8) equals sensitivity to the high frequency measurement noise $M_{n\infty}=\lim_{\omega\to\infty}|C_u(i\omega,q|$. However, when a second-order noise filter is applied in the PID controller $M_{n\infty}=0$. In this case, the sensitivity to measurement noise $M_{nz}=M_{n2}$ is defined by the integral

$$M_{n2}=\sqrt{\frac{1}{\omega_C}\int_\varepsilon^{\omega_c} C_u(i\omega,q)C_u(-i\omega,q)d\omega}\ , \tag{11}$$

and $\chi_{3d}=M_{n2d}$, for the band-limited measurement white noise $n_w(t)$ with the cutoff frequency ω_c. The measurement noise variance σ_n^2 is related to the control signal variance σ_u^2, induced by this noise, as $\sigma_u^2=M_{n2}^2\sigma_n^2$. The desired value M_{n2d} is obtained by the following procedure. Simulation of the closed-loop system defined by the PID_{tun} controller in the loop with the model $G_m(s)$ in (1), defined by the quadruplet $\{k_u, \omega_u, \varphi, A\}$, is performed with the band-limited white noise $n_w(t)$, added to the controlled variable. The noise $n_w(t)$ is obtained from the Band-Limited white noise generator defined by the "noise power" b_w=PSD and sample time T_s, discussed in detail in [8]. The cutoff frequency ω_c of this band-limited white noise is defined by

$$\omega_C=\frac{\pi}{T_s},T_s\approx\frac{T_{f0}}{N_C},N_C=2\ , \tag{12}$$

where T_{f0} is the value of the noise filter time constant in the PID_{tun} controller. From this simulation the initial value of the second-order noise filter time constant T_f in the PID_f controller with n=2, is determined as T_f=gT_{f0}. By simulation with the noise from the previous step, the parameter g is adjusted to obtain the desired reduction of the control signal activity, compared to that obtained by the PID_{tun} controller.

The performance/robustness tradeoff obtained by the PID controller optimization under constraints on the desired values of $M_{n2d}(M_{n\infty d})$, M_{sd} and M_{pd} has a clear physical interpretation. For the particular loop it is known what is the level of the measurement noise. Higher values of $M_{n2d}(M_{n\infty d})$ result into faster rejection of the load disturbance and into higher control signal activity, and vice versa. If the actuator requires the small control signal variation, the PID controller with n=2 must be applied. If the actuator tolerate significant control signal activity, PID with n=1 can be applied. Desired performance can be defined as fast rejection of the load disturbance obtained for higher values of M_{sd} and M_{pd}. Otherwise, and if greater variation of the dead-time or the process gain is expected, to obtain a robust tuning the user will specify the desired performance with lower values of M_{sd} and M_{pd}.

EXPERIMENTAL VERIFICATION OF PROPOSED CPA

When the quadruplet k_u, ω_u, φ, A and optimal parameters q of the controller $C(s,q)$ are determined, the desired set-point and load disturbance responses, obtained by using the model $G_m(s)$ in the loop with the controller $C(s,q)$, are compared with the responses obtained by the controller $C(s,q_0)$, applied to the same $G_m(s)$. If the evident improvement is obtained by the suggested structure and tuning, the controller $C(s,q)$ is applied to the process.

Experimental verification of the proposed CPA is performed by using a laboratory nonlinear thermal plant with noisy measurements [9], presented in Fig. 2. It consists of a thin aluminum plate, long L=0.1m and wide h=0.03m. The temperature $T(x,t)$, distributed along the plate, is measured by precision sensors LM35 (TO92), at positions x=0 and x=L. The plate is heated by the terminal adjustable regulator LM317 (TO 220) at x=0. The manipulated variable is the dissipated power of the heater at x=0. The input to the heater is the control variable $u(t)$[%], defined by the output of the controller, in the range $0\le u(t)\le 100\%$. The controlled variable is $y(t)=T(L,t)$, while measurement at x=0 is used to prevent overheating, to keep the temperature $T(0,t)\le 70^{\circ}$C [9,10].

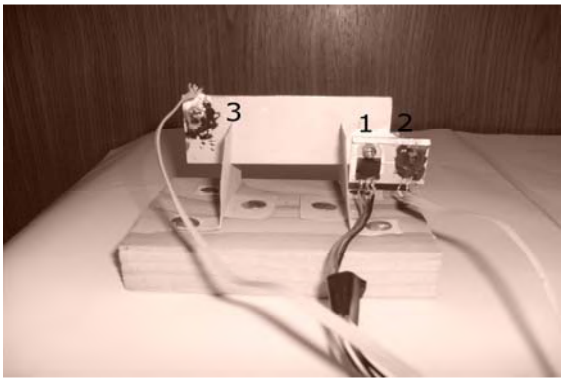

Fig. 2. Laboratory thermal plant with heater 1 at x=0. Temperature T(x,t) is distributed along the plate from x=0 to x=L. The controlled variable y(t)=T(L,t) is measured by the sensor 3. Temperature sensor 2 at x=0 is used in the safety device, to prevent overheating when T(0,t)≥70°C.

The evaluated controller is a PI controller with: k=6.3810, k_i=0.055 and b=0.66. The estimated model $G_m(s)$ is defined by k_{uest}=28.6582, ω_{uest}=0.04458, φ_{est}=0.6377, $G_{pest}(0)$=0.4104. The proposed PID controller with the second-order noise filter is obtained by analyzing three controllers. The first PID_{tun}, defined by: k_0=18.5110, k_{i0}=0.1976, k_{d0}=458.4715. T_{f0}=2.2422, is tuned for n=1 by applying tuning rules [8]. For this PID_{tun} controller M_s=2.05, M_p=1.48, $M_{n\infty}$=204.47. The second one PID_f is obtained for n=2 from the PID_{tun} as: k=18.5110, k_i=0.1976, k_d=458.4715, T_f=2.2422g, g=2, with resulting M_s=3.06, M_p=2.43 and M_{n2}=24.17, obtained from [8] for T_s=1. The third, proposed $optPID_f$ is obtained by PSO optimization for n=2, M_{sd}=2, M_{pd}=1.5 and M_{n2d}=24. It is defined by: k=13.3128, k_i=0.1692, k_d=380.8233, T_f=3.8764.

As demonstrated in Fig. 3a, nice performance obtained by the PIDtun controller results for this process into significant control signal activity in the presence of the measurement noise, as illustrated in Fig. 3b. A practically inapplicable control signal is obtained by the PIDtun controller, taking into account the constraint on the real plant, defined by $0\le u(t)\le 100\%$. Acceptable and significantly smaller variation of the control signal is obtained by the optPIDf compared to PIDtun, as demonstrated in Fig. 3b.

Also, by the proposed optPIDf controller, compared with the evaluated PI controller in Figs. 4a-b, a significant performance improvement is obtained with the acceptable control signal activity, as demonstrated in Fig. 4b. According to this analysis, the proposed optPIDf controller, is used for the further analyses. Responses obtained with this controller and with the evaluated PI controller in the loop with the real plant are presented in Figs. 4c-d.

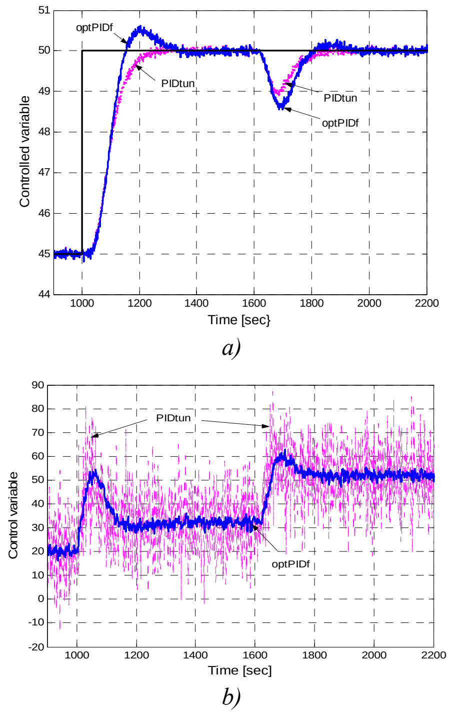

Fig. 3. Controllers in the loop with the model Gm(s) of the laboratory thermal process, a -20% change of the control signal is inserted at time t=1600s. Comparison of the PIDtun and the proposed optPIDf, band-limited white noise nW(t) is added, with PSD=0.003 and Ts=1.

CONCLUSION

The optimal PID controller, with the second-order noise filter, satisfying the desired performance and robustness, is obtained by simulation and by the constrained optimization, both based on the model $G_m(s)$ of the process in the evaluated loop. Simulation of the model $G_m(s)$ in the loop with the evaluated/proposed controller gives a reliable performance assessment and how far the evaluated controller is from the proposed optimal controller. Parameters used in this analysis have a clear physical interpretation and can be measured in the closed-loop experiment, without breaking the loop of the controller in operation. It is demonstrated by experimental results that the proposed CPA, performed by using the model $G_m(s)$, is confirmable on the plant.

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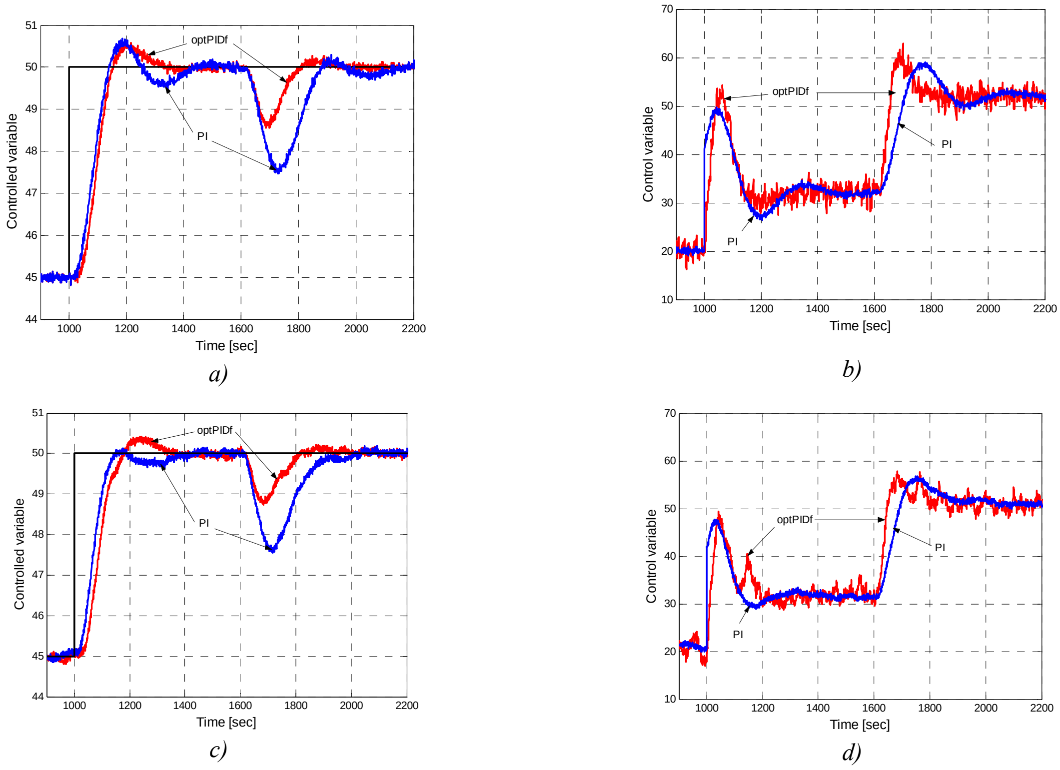

Fig.4. The laboratory thermal process: a)-b) Simulation results, the evaluated PI and proposed optPIDf controller in the loop with the model Gm(s), band-limited white noise nw(t) is added, with PSD=0.003 and Ts=1; c)-d) Real plant with the evaluated PI and proposed optPIDf controller. A -20% change of the control signal is inserted at time t=1600s

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