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***Abstract*—A novel autotuning procedure is presented through application to an industrial in-line pH control system. The procedure has three advantages over classical relay auto-tuners: experiment duration is very short (no need for limit-cycle convergence); all data is used for identification (instead of only peaks and switch instances); a parameter uncertainty model is identified and utilized for robust controller synthesis.**

I. INTRODUCTION

Most process industrial plants can be adequately controlled using either the PI or PID controller [1]. However, an accurate model of the process to be controlled is a pre-requisite for successful tuning of the controller. Obtaining such a model is usually time-consuming and expensive. A typical process industrial manufacturing plant has thousands of PID controllers, and consequently many of them are left poorly tuned [2].

The previous facts explains the popularity of automatic controller tuning methods, also known as autotuners. These methods combine an identification experiment with a controller tuning. The basic idea behind the most commonly used autotuner is to close a negative feedback loop over the plant in series with a relay, as shown in Figure 1. For most industrial processes, this results in a stable limit cycle oscillation close to the cross-over frequency of the plant [3]. This ability – to automatically produce an input signal with adequate excitation – is a key property of relay autotuners. Controller tuning is subsequently based on the switching time instants (the oscillation period) and peak values of the output (used to compute process gain) [4].

In this work an improved version of the relay method is utilized. It voids the requirement for limit cycle convergence, by using all recorded data, as opposed to only peak and switch values. Furthermore, the identification procedure which enables this also yields a parameter uncertainty model, which we utilize for robust controller synthesis.

This novel autotuner is applied to an in-line pH control system, which is commonly occurring in chemical production industry, and often regarded as difficult to control. A brief presentation of the pH control system is given in Section II. The novel autotuning procedure is then presented in Section III. Finally, the results of identification and control experiments carried out on the physical plant are shown in Section IV.

This paper presents the application to a real process of a novel autotuning procedure. Some elements of this novel

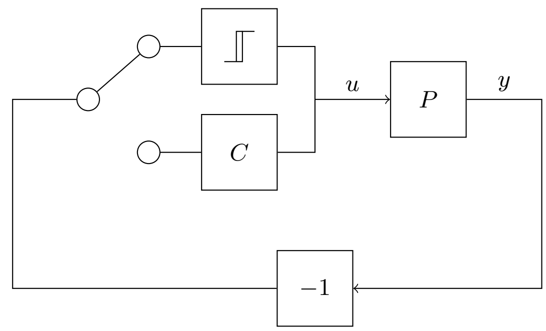

Fig. 1. Block diagram of relay autotuner with plant P, controller C, control signal u, and plant output y.

procedure have been published in [5] and [6]. Theoretical background, implementation issues and comparisons with other methods are discussed in a paper to appear.

II. THE IN-LINE pH CONTROL SYSTEM

The control of pH processes has motivated many works in the literature (see [7] and references therein). Most pH control loops are based on the Continuous Stirred Tank Reactor (CSTR) model, comprising a tank with an agitator used to reach a perfect mixture. Another possible setup is the in-line process, where mixing occurs in the production line itself [8]. This work deals with the latter. The considered experimental setups is part of a canned food industry pilot plant, shown in Figure 2. The pH control loop consists of the following elements:

- A tank where the product is stored;
- A progressive cavity pump that produces a continuous product flow;
- An electromagnetic metering pump[1] (LMI Milton Roy AA9), which injects acid into the product;
- A 350 mm long static mixer;
- A pH sensor (Endress & Hauser, Orbisint CPS 11).

The product is potable water from the water supply network, the acid is an aqueous solution of nitric acid with a 10%

[1]The pump can only make a natural number of strokes per minute (spm), between 0 and 100. At 100 spm, the pump creates a flow rate of 1.6 liters per hour (lph).

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Fig. 2. Photograph of the pilot plant containing the in-line pH control system.

concentration, and the steady product flow rate generated by the progressive cavity pump is around 300 liters per hour (lph). The identification and control experiments is carried out around the operating point defined by the control output 15 spm, and its corresponding steady state pH of 7. The sampling time of the controller is 0.5 s.

III. Autotuning Method

Relay autotuning methods are very common in industrial practice. A key feature of these methods is that they produce an experiment that excites the process at frequencies relevant for controller synthesis, without the need of a priori plant information. However, the classic relay autotuner only utilizes process output peaks and relay switch times for modeling. This makes it noise sensitive, and requires convergence of a stable limit cycle. These caveats can be overcome by utilizing the entire experiment data set, as suggested in [5], and adopted in this work.

A. Identification

The use of an asymmetric relay (aka biased-relay) has been proposed in the literature for obtaining better signal excitation than the obtained by the symmetric relay (see for example [9]–[11]). The proposed experiment utilizes an asymmetric relay, with output levels $u_{\text{on}} = -\gamma u_{\text{off}}$, and $\gamma = 1.5$, as suggested in [12]. However, instead of the 6–8 switches typically needed for convergence, the experiment is terminated after only 3 switches.

The relay hysteresis is set according to the level of noise in the process output. Assuming white noise with zero mean and variance σ_n^2, the hysteresis level $\mu = 2\sigma_n^2$ is recommended. Due to the reverse characteristic of the process (increment of spm implies a decrement in pH) a positive feedback loop is used during relay experiments.

After performing the asymmetric relay experiment, the plant input u and output y, sampled at period h, are used to estimate parameters $\theta = [k\ \tau\ L]^\top$ corresponding to the FOTD model structure:

$$\hat{P}(s) = \frac{k}{\tau s + 1} e^{-sL}. \tag{1}$$

Continuous time representation is utilized to limit the number of elements of the parameter vector θ.

The parameters identification procedure is posed as an optimization problem, as suggested in [13], aiming to minimize the output error $\mathcal{L}_2$-norm:

$$J(\theta) = \frac{1}{2}\int_0^{t_f} e^2(t)dt, \tag{2}$$

where $e = y - \hat{y}$, $\hat{y}$ is the resulting output when $\hat{P}$ is driven by u, and t_f is the experiment duration. The optimization is handled by an active-set solver. To improve convergence, the exact parameter sensitivity gradient and an approximation of the corresponding Hessian are provided in each iteration. Technical details surrounding the computations yielding these expressions are available in [5].

In addition to the expectation $\bar{\theta}$, the optimization provides the asymptotic covariance matrix

$$R_{\bar{\theta}} = \mathbb{E}\left[(\theta - \bar{\theta})(\theta - \bar{\theta})^\top\right] = \frac{2}{N}\bar{J}(\Delta\bar{J})^{-1}, \tag{3}$$

where N is the number of samples [14]. The standard deviations of the parameter estimates decrease $\propto 1/\sqrt{N}$, meaning that one cannot expect significantly improved estimation precision, by (small) increases in experiment duration.

B. Controller Design

Upon obtaining estimates of the parameter expectations and covariances, a control design problem is formulated. The aim is to synthesize a PI controller, robust to the model uncertainty, as expressed through the parameter covariance matrix (3). The controller is parametrized in continuous time as

$$C(s; x) = k_p + \frac{k_i}{s}, \tag{4}$$

where $x = [k_p\ k_i]^\top$ is the vector of controller parameters. The synthesis problem formulation is based on propagating the model uncertainty (assuming that model parameter uncertainty obeys a multivariate Gaussian distribution) through to a performance index, which is optimized, and robustness indices, which are constrained. A common performance index, quantifying disturbance attenuation (the main concern in process control), is the integrated absolute error (IAE):

$$\text{IAE} = \int_0^\infty |e(t)|dt, \tag{5}$$

where $e(t)$ is the error due to a unit step disturbance entering at the plant input. Analytic computation of the IAE is very seldom possible. As a tractable alternative it is common to use the integrated error (IE):

$$\text{IE} = \int_0^\infty e(t)dt. \tag{6}$$

This choice simplifies the problem since minimization of (6) is equivalent to maximization of the integral gain, k_i in (4), as pointed out in [15]. The IAE and IE coincide for control loops with non-oscillatory load step responses, and are similar for loops with well-damped responses. The latter is a desirable feature, and it can be enforced by imposing robustness constraints. Herein this is achieved by stochastic $\mathcal{H}_\infty$ constraints on the sensitivity, $S = (1 + \hat{P}C)^{-1}$, and complementary sensitivity, $T = 1 - S$.

Motivated by the above requirements, the control design problem is posed as the following stochastic optimization problem:

$$\begin{aligned}
&\underset{x=[k_p\ k_i]^\top}{\text{maximize}} && k_i, \\
&\text{subject to} && \mathbb{E}\left[\|S(\theta,x)\|_\infty\right] + \alpha_s\sqrt{\mathbb{V}\left[\|S(\theta,x)\|_\infty\right]} \le M_s, \\
& && \mathbb{E}\left[\|T(\theta,x)\|_\infty\right] + \alpha_t\sqrt{\mathbb{V}\left[\|T(\theta,x)\|_\infty\right]} \le M_t.
\end{aligned} \tag{7}$$

The design parameters α_s and α_t let the user specify the confidence with which each robustness constraint should be met. Note that when there is no uncertainty, i.e. zero covariance matrices, the design problem (7) is equivalent to the well-known MIGO approach for PI design [15].

Robust PI(D) design for processes with stochastic parametrization has been recently studied in [6], to which the reader is referred for details concerning the solution of (7).

IV. Experimental results

In this section we demonstrate the proposed autotuning method on the industrial in-line pH control loop described in Section II.

The identification experiment was carried out using relay output levels $u_{\text{on}} = 5$ and $u_{\text{off}} = -\gamma u_{\text{on}} = -7.5$ (corresponding to $\gamma = 1.5$, as previously mentioned). Taking operation point offset and quantification of the control signal into account, the corresponding control signal values become 20 and 7, respectively. The relay hysteresis was set to 0.025.

The proposed experiment and identification procedure yielded the parameter vector $\theta = [k\ \tau\ L]^\top = [-0.067\ 33.7\ 26.5]^\top$ (and corresponding covariance matrix). The gain k is given in spm^{-1}; while the time parameters, τ and L, are given in seconds. A much longer (700 vs 122 s) step response experiment yielded a very similar model parametrized by $\theta = [k\ \tau\ L]^\top = [-0.068\ 30.8\ 20.3]^\top$), as shown in Figure 3.

Next, the optimization problem (7) was solved, using the design parameters $\alpha_s = \alpha_t = 1$ and $M_s = M_t = 1.5$. The obtained vector of controller parameter, $x = [-7.379\ -0.247]^\top$, was implemented on an industrial controller. Figure 4 shows both the experimental and simulated disturbance attenuation capabilities of the resulting closed-loop system. (The load disturbance resulting in the response of Figure 4 was a pulse of height -8, active from the instance 50 to 500.)

V. Conclusion

This short paper has presented the successful application of a novel autotuning method on an in-line pH control system. The method combines a modified relay experiment, output error identification and controller design. Its main strengths lie in the short experiment duration, combined with a robust synthesis method, explicitly accounting for identified model parameter uncertainty.

While theoretical aspects of the method have been previously presented by the authors [6], this paper demonstrates its industrial relevance through evaluation on a process representative of industrial production plants.

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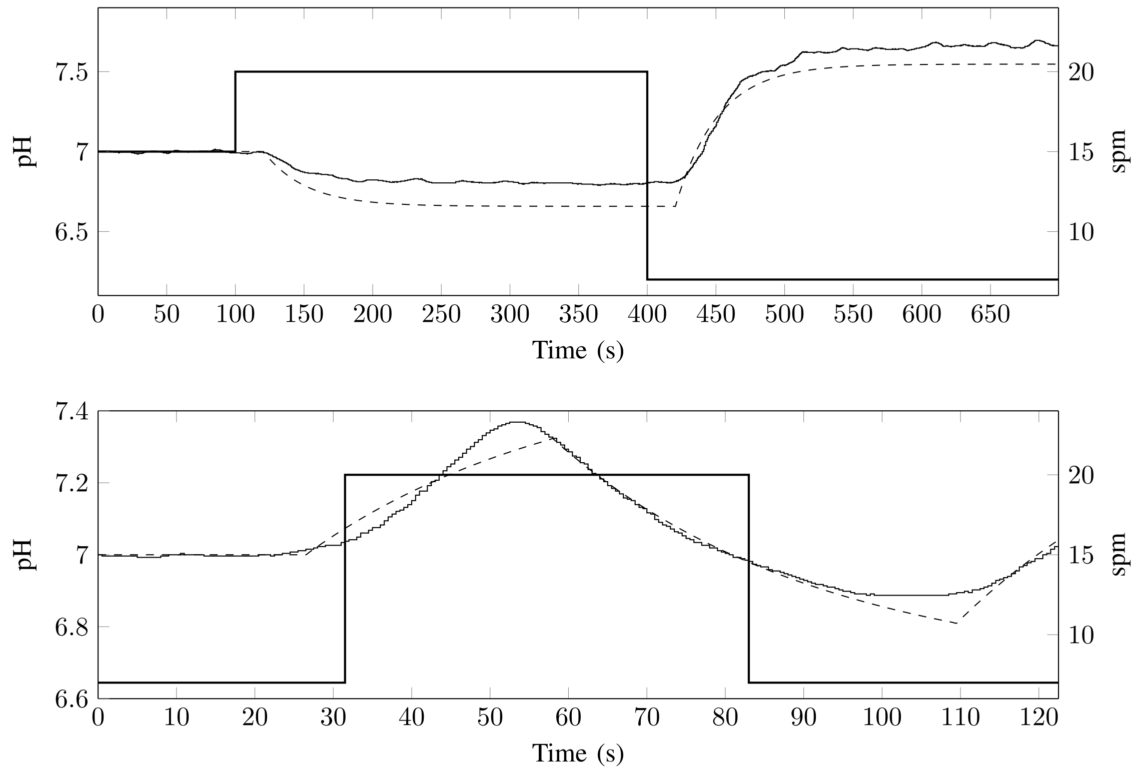

Fig. 3. Identification experiments: step response (top) and relay (bottom). Curves show measured output (solid thin), simulated output of the identified model (dashed), and input (solid thick).

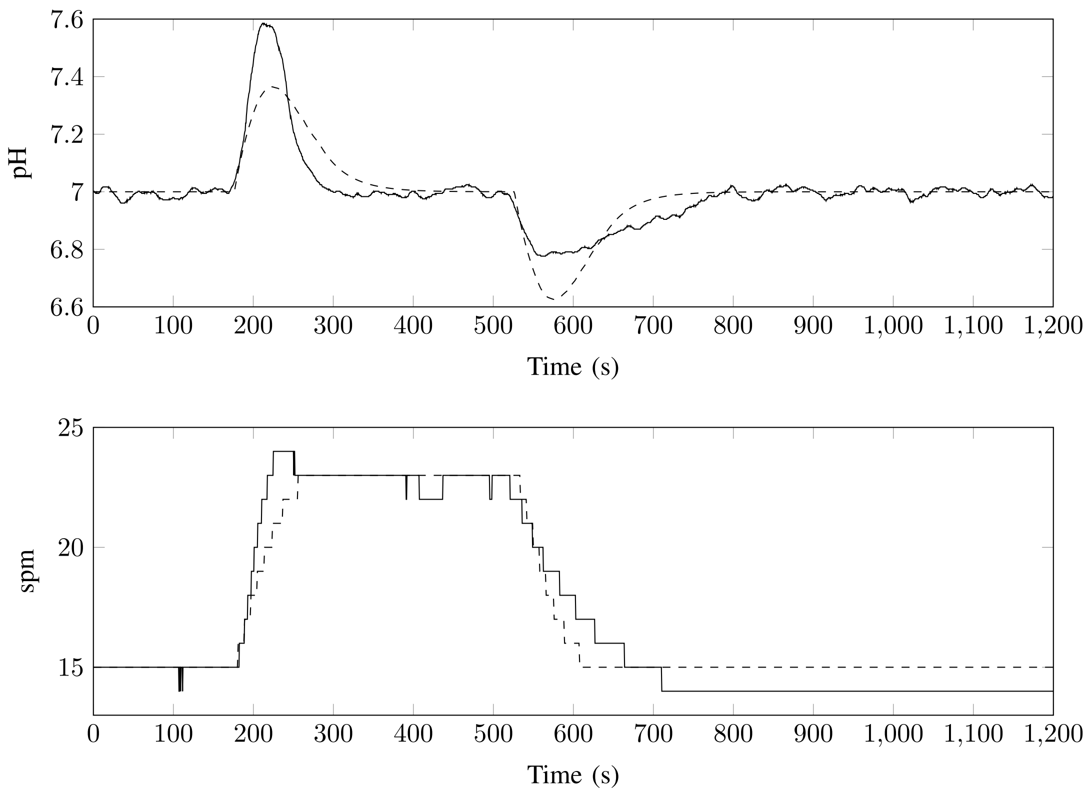

Fig. 4. Closed-loop load disturbance attenuation experiment: plant output (top) and controller output (bottom). Experimental data is shown in solid, simulated in dashed. The disturbance enters at the plant input as a pulse of height -8 being active from the instant 150 to 500.