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Next Generation Relay Autotuners – Analysis and Implementation

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Abstract— **In order to produce models for automatic controller tuning, this paper proposes a method that combines a short experiment with a novel scheme for approximating processes using low-order time-delayed models. The method produces models aimed to tune PI and PID controllers, but they could also be used for other model-dependent controllers like MPC. The proposed method has been evaluated in simulations on benchmark processes. It has also been implemented in an industrial controller and tested experimentally on a water-tank process. It is shown that our method is successful in estimating models for a variety of processes such as lag-dominated, delay-dominated, balanced, and integrating processes. We also demonstrate that the experiment time is both shorter and more predictable than currently used autotuners.**

I. Introduction

Research, development, and implementation of automatic tuning procedures for PID controllers started at almost the same time at the beginning of the 1980's. There were two main reasons for this. The first one was the great need for this kind of procedures, since tuning of PID controllers was considered a difficult and time-consuming work in process control. The second reason was that analogue instrumentation was replaced by computer-based instruments at this time, providing the possibility to implement more advanced functions in controllers and control systems. A lack of research done in this area prior to this time led to research starting at about the same time as implementations in industry. While lots of research had been done on system identification and adaptive control during the preceding decades, the results were not suitable for automatic PID controller tuning.

Most autotuners in industrial control systems are today based on the method presented in [1]. The method identifies the critical point on the Nyquist curve where the phase is close to $-180°$. This point is identified using a relay method that works as an on-off controller that makes the system converge towards a steady state oscillation. The critical point is determined from the period and amplitude of this oscillation. This method was developed when the available computing power was severely limited compared to today. Even though it works well in many cases, it has limitations and it can be improved in several ways. First of all, the fact that only one frequency point is identified limits the controller design possibilities. Other drawbacks are that the system has to be stationary before the experiment starts, and that the required experiment time may be unnecessarily long, which leads to a higher risk for disturbances occurring during the experiment.

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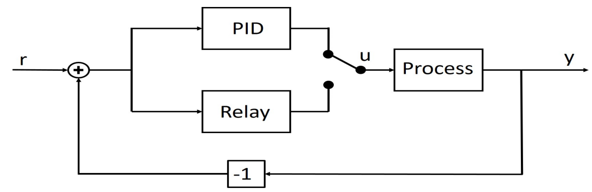


Fig. 1. Conceptual block diagram for PID relay autotuners.

A relay autotuner based on [1] is included in the ABB AC 800M controller family, the primary controllers in the process automation system ABB Ability™ System 800xA. A conceptual block diagram of the relay autotuner is shown in Fig. 1. When the autotuner is started, it switches the control signal from PID control to the relay signal. When the experiment is finished, the control signal is switched back to PID control and new PID parameters are suggested.

As more computing power has become available, it is now possible to use more of the information gained from the experiments, and many extensions and improvements of the method presented in [1] have been proposed. For instance, [2] and [3] modified the autotuner to find low order models of the process instead of just one frequency point. The excitation of the process has also been improved by the use of asymmetric relay functions in e.g., [4] and [5]. A review of methods for process modelling from relay experiments can be found in [6].

The work in [7] describes a short relay experiment. It can be started from a non-stationary point and uses an asymmetric relay to excite a wide range of frequencies. There, optimisation is used to fit second-order time-delayed models to experimental data. These models are then used to tune PI and PID controllers. It is shown that with only three relay switches a model can be estimated.

This paper describes an adaptation of the method proposed in [7] and its implementation in an industrial controller, as well as provides an evaluation of the implementation. We discuss how the system identification is impacted by: 1) the number of relay switches and 2) an extension of the experiment. Overall, our objective was to obtain a method, with a short experiment time, which is easy to use and provides system models that can also be used for more complex control structures, such as model predictive control

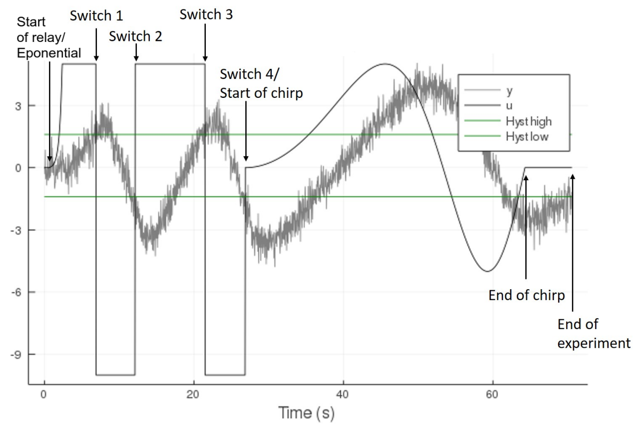


Fig. 2. An example experiment with four relay switches and a relative chirp length of four that is, 4 times the time between switch 2 and switch 3. Here, y is the measured signal, u is the control signal, and $Hystlow$, $Hysthigh$ are the lower and upper hysteresis levels used for the relay experiment.

(MPC).

The proposed method was evaluated first through a simulation study on the test batch in [8] consisting of 134 process transfer functions. Our implementation on the ABB AC 800M controller allowed us to compare the existing AC 800M relay autotuner with our new proposed method on a physical process; water level control in a double tank. Our results show that a relay autotuner based on [7] together with our modifications works well, both in simulation and on physical process. In simulations, the identified transfer functions were close to the simulated models both in amplitude and phase, especially around the critical frequency. On the physical process, the experiment time was both shorter and more predictable for the proposed method than for the existing autotuner.

II. Problem setup

The experiment designs that we consider throughout this paper are both pure relay experiments and relay experiments followed by a sinusoid in which the frequency is swept, also known as a *chirp*. An example experiment design is shown in Fig. 2, where four relay switches are followed by a chirp.

When the experiment was implemented we primarily focused on: 1) how the experiment was designed, 2) how to perform model estimation, and 3) how the models were evaluated afterwards. We describe these three aspects below.

A. Experiment Design

1) Hysteresis design: The hysteresis is used to ensure that the relay switches are triggered by a process value deviation rather than due to inherited randomness in the process such as measurement noise. Therefore, a natural step was to base the hysteresis level on the measurement signal noise. For this purpose, we assume that the process is drifting linearly as $y(t) = at + b + \eta(t)$, where $\eta(t)$ is white measurement noise with standard deviation σ_η. Then, at the start of the experiment the measurement noise variance can be estimated from the one step difference with step length h as

$$\begin{aligned}\mathrm{Var}[e(t)] &= \mathrm{Var}[y(t) - y(t-h)] \\ &= \mathrm{Var}[at + b + \eta(t) - (a(t-h) + b + \eta(t-h))] \\ &= \mathrm{Var}[ah + \eta(t) - \eta(t-h))] \\ &= 0 + \sigma_\eta^2 + \sigma_\eta^2 \\ &= 2\sigma_\eta^2.\end{aligned}$$

In order to limit the data stored in the AC 800M controller, we estimate the variance of the one step difference $e(t)$ recursively using Welford's online algorithm [9]. The estimated variance was then used to design an appropriate hysteresis level. Based on experimentation, the hysteresis level was set to $y_0 \pm 3\sigma_\eta$, which ensured a sufficient signal-to-noise ratio and also made it possible to statistically test if the signal was significantly different from y_0. With this hysteresis level, however, there remains a risk for false triggers. This risk was lowered by also including a low pass filter on the form

$$\tilde{y}(t) = c\tilde{y}(t-h) + (1-c)y(t), \tag{1}$$

where $\tilde{y}$ is the low-pass filtered signal and c is a constant. The filtered signal can be ensured to have a desired variance $\mathrm{Var}[\tilde{y}] = \sigma_{\mathrm{des}}^2$ by choosing

$$c = \frac{1-x}{1+x}, \tag{2}$$

where $x = \sigma_{\mathrm{des}}^2/\sigma_\nu^2 \leq 1$. In this work, we chose to set $x = 0.01$ as it yielded consistent and well-behaved relay switches. Note that throughout this paper $\tilde{y}$ is only used for the timing of the relay switches.

2) Relay experiment: As suggested in [1], the relay experiment is started with an exponential ramping in the control signal, which can also be seen in Fig. 2. The exponential start makes it possible to run the experiment on processes that are sensitive to small deviations in the control signal. If the hysteresis is hit before the exponential ramp has reached its maximum allowed value, the control signal is adjusted to have a lower amplitude. Furthermore, the relay output levels are asymmetric according to $[u_0 - \gamma\Delta u, u0 + \Delta u]$, as proposed in [7]. Here, we chose $\gamma = 2$. The asymmetry can be seen in Fig. 2 where the control signal u switches between $[-5\gamma, 5] = [-10, 5]$. Asymmetry is used to excite a wider spectrum of frequencies around the critical frequency.

3) Chirp design: A chirp was introduced to ensure adequate input excitation over the frequency range of interest. A general formula for a chirp is

$$u_{\mathrm{chirp}}(t) = A\sin(t\omega(t)), \tag{3}$$

where A is a constant and $\omega(t)$ is a time-dependent angular frequency. In this work, the chirp was introduced to further excite the frequencies below the critical frequency of the system. When conducting an experiment, the critical frequency is in general unknown and therefore has to be estimated. Using the main idea of [1] that a relay experiment approaches a self-oscillation, a lower bound on the critical frequency can be estimated by regarding the longest time, T_{period}, between two subsequent relay switches. In our experiments the chirp angular frequency varies linearly between 0 Hz and $1/(4T_{\text{period}})$. To have a standard time unit for an identified process, T_{period} was used, so that a *relative chirp length* of 2 corresponds to the chirp experiment being $2T_{\text{period}}$ long. How this is applied can be seen in the example experiment in Fig. 2 where a relative chirp length of 4 is used.

B. Model estimation

Once the data has been sampled the next key question is: how should a model be estimated using the data? Here, the approach in [7] was followed in the sense that the aim was to fit low-order models to match the sampled data. The chosen models were:

$$P_{FOTD} = \frac{b_0}{s + a_0} e^{-Ls} \tag{4a}$$

$$P_{SOTD} = \frac{b_0}{s^2 + a_1 s + a_0} e^{-Ls} \tag{4b}$$

$$P_{SOZTD} = \frac{b_1 s + b_0}{s^2 + a_1 s + a_0} e^{-Ls}, \tag{4c}$$

where L, a_0, a_1, b_0, and b_1 are constants. These models were chosen as they are of low orders, which made them suitable both for PID design as well as for more advanced control laws such as MPC.

Fitting the models in (4) to measurement data is a non-convex problem. This leads to difficulties with local minima when trying to fit model parameters through optimisation. Occasionally, the solutions found through standard methods were insufficient for our purposes. To cope with this problem, we design a method to derive a good initial value for the underlying model. The idea is to introduce a smooth and twice continuously differentiable function which optimally approximates the measurement data. More precisely, we seek to find the function $g(t)$ which minimises the cost

$$J_\alpha(g) = \alpha \sum_{i=1}^{N} (y_i - g(t_i)^2) + (1-\alpha) \int_{t_0}^{t_n} g''(t)^2 dt, \tag{5}$$

where $\alpha \in (0, 1]$ is a constant and y_i is the ith measurement sample at time t_i. It can be proven that for any twice differentiable function g which minimises J_α the points $\{x_i, g(x_i)\}_i$ can also be interpolated using a cubic spline and this interpolation would then have at most the same cost. When the function g in (5) is restricted to cubic interpolating splines then, given two boundary conditions, the minimiser is unique and can be found as the solution of a linear equation. In (5), α has a large impact on the resulting fit. Therefore, cross-validation is used to find an optimal α for the sampled data. Afterwards, both the control signal u and the measurement signal y are approximated by a corresponding cubic spline $\hat{u}$ and $\hat{y}$. Then the transfer functions in (4) are used to formulate their corresponding differential equations:

$$\hat{y}'(t) + a_0 \hat{y}(t) = b_0 \hat{u}(t - L) \tag{6a}$$

$$\hat{y}''(t) + a_1 \hat{y}'(t) + a_0 \hat{y}(t) = b_0 \hat{u}(t - L) \tag{6b}$$

$$\hat{y}''(t) + a_1 \hat{y}'(t) + a_0 \hat{y}(t) = b_1 \hat{u}'(t - L) + b_0 \hat{u}(t - L). \tag{6c}$$

From these equations a least-squares problem is formulated for a given L, using the approximated values $\hat{u}(t - L)$ and $\hat{y}(t)$. Performing the least-squares estimation yields approximate values of the parameters (a_1, a_0, b_1, b_0) for each L. By iterating through a grid of candidate L values it is possible to find a set of these parameters which minimises the squared error. These parameter values are then used as initial values when starting the non-linear optimisation. For the application considered in this paper, this method reduced the problem with poor initialisations and undesirable local minima.

In our implementation, the models were fit using optimisation algorithms available in the package NLopt [10] for Julia. The used optimisation algorithms are based on [11] and [12].

C. Evaluation

When the optimisation has been run, there is one final question: how should the fits be evaluated? In this work, we use three metrics to evaluate our results:

i. Mean squared error (MSE); is the fit good in the time domain?
ii. Bode diagrams; is the fit good in the frequency domain?
iii. The ν-gap metric; how close is the estimated model to the real?

The MSE indicates if the optimisation has been successful in fitting a curve to the data. This metric is therefore used to assess the quality of the curve fitting in the time domain.

Next, in cases where the excitation of a process is low it is possible that two processes with quite different transfer functions yield similar time adaptations, despite being different. To reveal such differing dynamics, we also analyse the fittings in the frequency domain. This is, in particular, possible in situations when the real process is known, which is the case when the data is simulated. Here, Bode diagrams are used to compare the models.

Another method to analyse the fit in the frequency domain is the Vinnicombe metric, also referred to as the ν-gap metric [13]. This is used to get an easily comparable measure of how well an estimated model matches the frequency properties of a known system.

To define the ν-gap metric, we first need to define the chordal distance between two transfer functions:

$$\delta_{P_1,P_2}(\omega) = \frac{|P_1(j\omega) - P_2(j\omega)|}{\sqrt{1 + |P_1(j\omega)|^2}\sqrt{1 + |P_2(j\omega)|^2}} \tag{7}$$

where $P_1(s)$ and $P_2(s)$ are transfer functions [14, Chapter 13]. In this paper, with a slight abuse of terminology, we take the ν-gap metric to be the maximum chordal distance over all frequencies

$$\delta_\nu(P_1, P_2) := \sup_\omega \delta_{P_1,P_2}(\omega). \tag{8}$$

The metric (8) indicates how close two transfer functions are over the span of all frequencies. A value close to 1 shows that the transfer functions are very different and a value close to 0 shows that they are close.

Fig. 3. A picture of the water tank process.

III. IMPLEMENTATION

Our method consists of

A. Experiment design
B. Model estimation
C. Evaluation.

The method was tested both in simulation and on a real process. For the simulation, the method was run against a test batch consisting of 134 models encountered in process control applications, suitable for PID control. The batch is presented in [8] and it includes lag-dominated, delay-dominated, balanced and integrating processes.

To evaluate the method on a real process, we ran it against the water tank process displayed in Fig. 3. The water tank process consists of two tanks placed on top of each other. A pump moves water into the upper tank, which has a hole at the bottom allowing water to flow into the lower tank. The lower tank, in turn, allows water to escape through a hole at the bottom. In this setup, the water level can be measured in both tanks and the voltage to the pump (and thereby the inflow to the upper tank) can be controlled.

We implemented the variance estimation and the relay and chirp experiments on ABB's AC 800M controller in order to apply it to the water tank process. The code was implemented in a development environment called Compact Control Builder, which supports the IEC standard 61131-3, specifying five programming languages [15]. Of these five, Structured Text and an ABB specific diagram language called Function Diagrams were used to implement the experiment. The optimisation to find the best low-order time-delayed models was performed through an external routine in Julia in the manner described in Section II-B.

TABLE I
NAMES USED IN THE PLOTS THROUGHOUT THE RESULTS SECTION.

FOTD, SOTD, SOZTD	Identified model type from (4): first/second order with (zero) time delay.
HystHigh and HystLow	Upper and lower hysteresis levels.
Relative chirp length x	The chirp duration is $x \times T_{\text{period}}$.
Real y	The measured process value.
no noise y	The measured process value without added noise.
u*n	The control signal u scaled by a factor n.

We compared our method with the existing relay autotuner in the ABB AC 800M controller. Since the existing method does not estimate a full model, the methods were compared in terms of their experiment time, and their performance when subject to two tests: a reference step test and a load disturbance test. These tests compared PI-parameters obtained from the existing autotuner with the AMIGO method [8] on a model from our model estimation.

IV. RESULTS

This section presents our simulated and experimental results. Table I summarises the abbreviations and acronyms used in the figures.

A. Simulation

The proposed method was run on the entire batch of transfer functions found in [8]. For the test batch, the curve fits were good for all models and the MSE was consistently low in comparison to the present noise. Fig. 4 shows the ν-gap metric, averaged over three runs with three different random seeds. From the average behaviour we can deduce that the experiment performing the best with regards to the ν-gap metric is the combination of two relay switches and a relative chirp length of two (Rel2Ch2 in the figure). The combination of three relay switches performs roughly the same, but with a shorter experiment time. The experiment with only two relay switches performed well for most of the models. However, it performed notably worse than the other experiments for the more extreme models such as 1-3, 19-23, 38-42, and 54-58 from the batch in [8].

Two representative simulation results on model 41, with transfer function

$$P_{41} = \frac{e^{-s}}{(1 + 200s)^2}, \tag{9}$$

are shown in Figs. 5 and 6. The first uses only two relay switches and the second has an additional chirp with a relative length of 2. The MSE and the ν-gap metric from the simulations are shown in Table II. The plots illustrate well the typical benefit of adding a chirp, namely that the model fit becomes better at low frequencies.

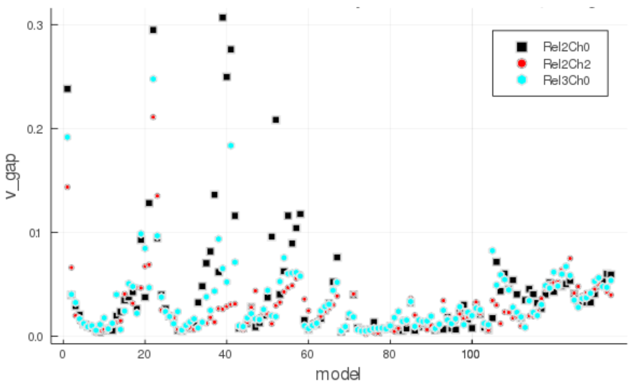
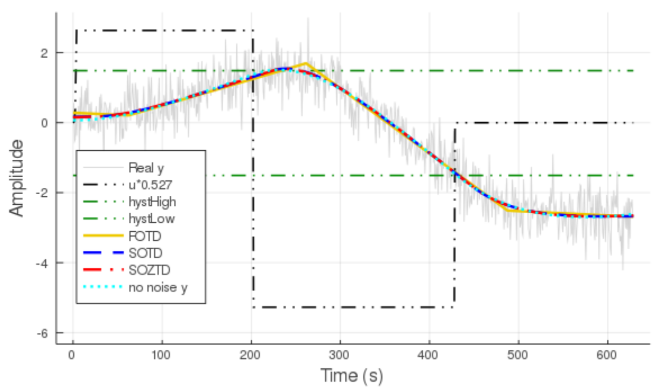
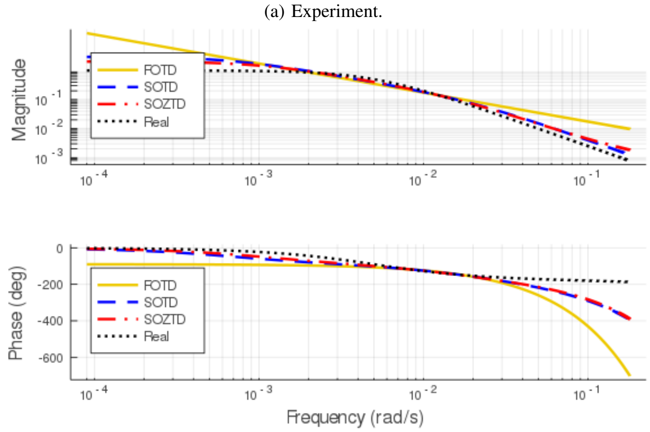


Fig. 4. The average ν-gap metric for each model in the test batch using three different random seeds for the simulation of each model. Three experiment designs are displayed; Rel2Ch0: two relay switches with no chirp, Rel2Ch2: two relay switches with relative chirp length of two, and Rel3Ch0: three relay switches with no chirp.

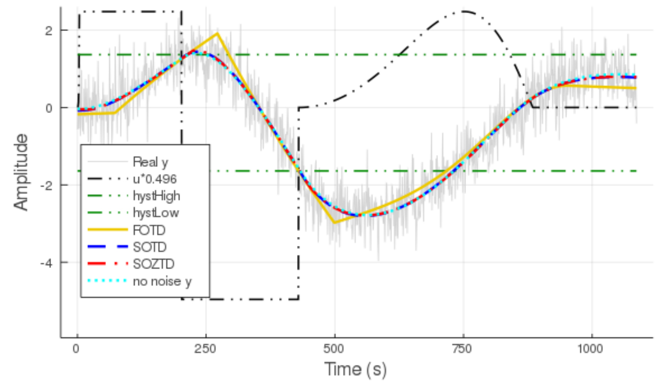


(a) Experiment.

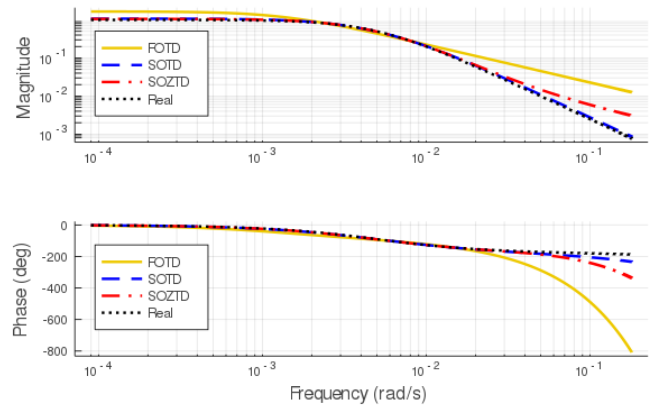


(b) Bode plot.

Fig. 5. Experiment and Bode plots for the estimations of Model 41 from the batch presented in [8], using two relay switches and no chirp.



(a) Experiment.



(b) Bode plot.

Fig. 6. Experiment and Bode plots for the estimations of Model 41 from the batch presented in [8], using two relay switches and a relative chirp length of two.

TABLE II

RESULTS FROM THE EXPERIMENTS IN FIGS. 5 AND 6 WITH AND WITHOUT THE USE OF CHIRP SIGNALS. THE MSE RESULTS WITHOUT CHIRP INDICATE A GOOD FIT, BUT THE ν-GAP REVEALS THAT THE UNDERLYING MODEL WAS NOT IDENTIFIED. THE RESULTS WITH CHIRP SHOW THAT THE ADDITIONAL EXCITATION YIELDS BETTER ESTIMATIONS.

	Without chirp		With chirp	
	MSE	ν-gap	MSE	ν-gap
FOTD	0.25	0.71	0.28	0.24
SOTD	0.25	0.44	0.25	0.04
SOZTD	0.25	0.32	0.25	0.03

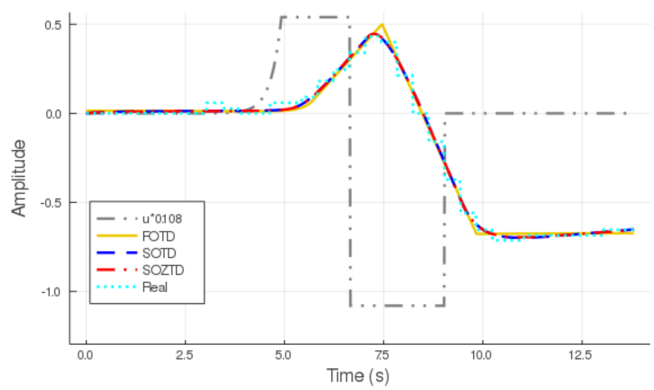
B. Results on water tank process

1) Upper tank: A short and a long experiment were performed on the upper tank. The identified transfer functions and the respective MSE are shown in Table III. The transfer functions from the short and long experiment are quite similar, especially in the frequencies close to the identified critical frequency. The short experiment consisted of two relay switches and is also shown in Fig. 7. Here it is also shown that all identified models fit the experiment data

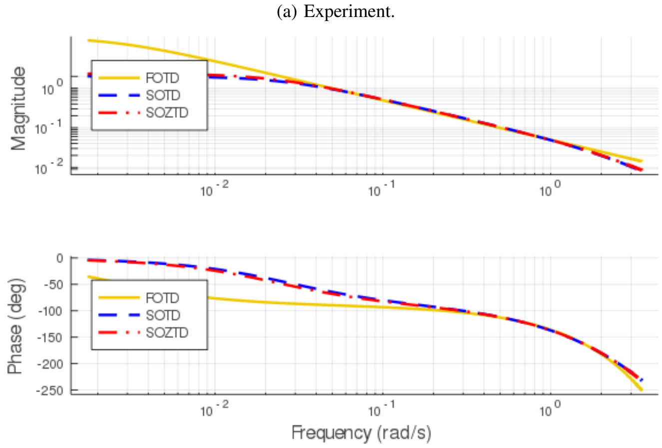
TABLE III

RESULTS ON THE UPPER AND LOWER WATER TANKS FOR, RESPECTIVELY, SHORT AND LONG EXPERIMENTS. FOR THE UPPER TANK, THE EXPERIMENTS WERE: TWO RELAY SWITCHES (SHORT), FIVE RELAY SWITCHES AND RELATIVE CHIRP LENGTH OF FOUR (LONG). FOR THE LOWER TANK: TWO RELAY SWITCHES AND RELATIVE CHIRP LENGTH OF TWO (SHORT), FOUR RELAY SWITCHES AND RELATIVE CHIRP LENGTH OF TWO (LONG). NOTE THAT THE MSE FROM THE SHORT AND LONG EXPERIMENT ARE NOT IMMEDIATELY COMPARABLE AS IT IS MORE DIFFICULT TO FIT A MODEL FOR A LONGER TIME SERIES.

Upper tank	Short experiment MSE	Short experiment Model	Long experiment MSE	Long experiment Model
FOTD	$1.1 \cdot 10^{-3}$	$\frac{0.05}{s + 2 \cdot 10^{-3}} e^{-0.8s}$	$2.3 \cdot 10^{-2}$	$\frac{0.05}{s + 0.02} e^{-1.7s}$
SOTD	$0.8 \cdot 10^{-3}$	$\frac{0.1}{s^2 + 2s + 0.06} e^{-0.4s}$	$2.3 \cdot 10^{-2}$	$\frac{0.06}{s^2 + 1s + 0.02} e^{-0.9s}$
SOZTD	$0.8 \cdot 10^{-3}$	$\frac{-2 \cdot 10^{-3} s + 0.1}{s^2 + 2s + 0.07} e^{-0.3s}$	$2.3 \cdot 10^{-2}$	$\frac{0.2s + 0.3}{s^2 + 6s + 0.09} e^{-2.0s}$
Lower tank	**Short experiment MSE**	**Short experiment Model**	**Long experiment MSE**	**Long experiment Model**
FOTD	$19 \cdot 10^{-3}$	$\frac{0.01}{s} e^{-14s}$	$88 \cdot 10^{-3}$	$\frac{0.01}{s} e^{-15s}$
SOTD	$0.4 \cdot 10^{-3}$	$\frac{8 \cdot 10^{-4}}{s^2 + 0.03s + 1 \cdot 10^{-3}} e^{-1.0s}$	$0.8 \cdot 10^{-3}$	$\frac{6 \cdot 10^{-4}}{s^2 + 0.03s + 3 \cdot 10^{-4}} e^{-0.9s}$
SOZTD	$1.2 \cdot 10^{-3}$	$\frac{-4 \cdot 10^{-4} s + 5 \cdot 10^{-4}}{s^2 + 9 \cdot 10^{-3} s + 3 \cdot 10^{-3}} e^{-0.3s}$	$0.8 \cdot 10^{-3}$	$\frac{-1 \cdot 10^{-4} s + 6 \cdot 10^{-4}}{s^2 + 0.03s + 3 \cdot 10^{-4}} e^{-0.7s}$



(a) Experiment.



(b) Bode plot.

Fig. 7. Experiment and Bode plots for the estimations of the upper tank process, using two relay switches and no chirp.

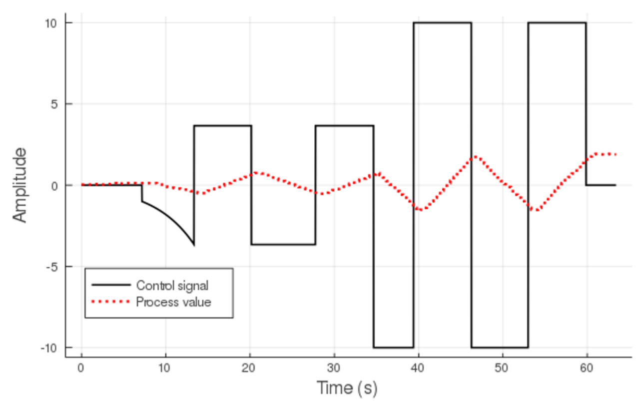


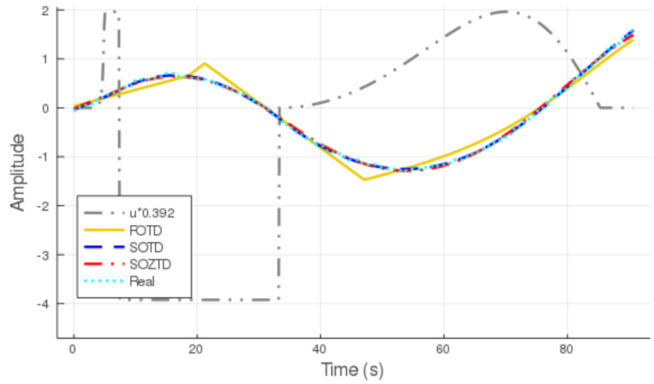
Fig. 8. The existing ABB AC 800M relay autotuner experiment on the upper tank.

well and that they agree around the critical frequency. This indicates that a short experiment is, in this case, sufficient to get an accurate model of the most relevant dynamics.

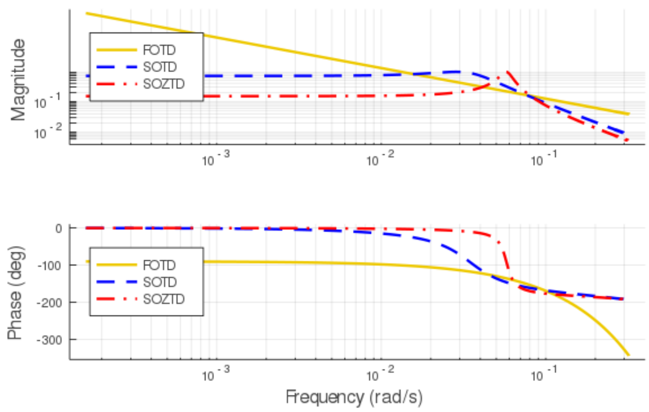
Fig. 8 shows an experiment using the current relay autotuner in AC 800M. Here it is worth noting the difference in experiment time between the proposed experiment and the one that is currently used.

C. Lower tank

A short and a long experiment were also performed on the lower tank. MSE and identified transfer functions are shown in Table III. The identified models from the short and long experiment were close, especially around the critical frequency. This indicates that a short experiment was sufficient for the lower tank as well. The short experiment consisted of two relay switches and a relative chirp length of two. The result is shown in Fig. 9. Here, one should note



(a) Experiment.



(b) Bode plot.

Fig. 9. Experiment and Bode plots for the estimations of the lower tank process, using two relay switches and a relative chirp length of two.

that the experiment shows second-order dynamics, which explains why the FOTD model cannot provide as good a fit as the other models. Still, all models agree around the critical frequency, which is most important.

The existing autotuner was also used on the lower tank and the result is shown in Fig. 10. The experiment displayed a similar result to the one for the upper tank. The results in Figs. 9 and 10 show that our experiment time was shorter and more predictable, since the number of relay switches and the relative chirp length were defined from the start. The existing autotuner, however, would use four to nine relay switches.

D. Comparison between existing and proposed autotuner

The existing ABB AC 800M relay autotuner was also compared to our method. We tuned a PI controller based on the SOTD model found from the short experiment on the upper tank, which is presented in Table III. The tuning was performed using the AMIGO method in [8]. The found PI parameters are given in Table IV together with the PI parameters found using AC 800M's existing relay autotuner. Here, K and T_i are parameters of the PI controller's transfer function

$$C_{PI} = K\left(1 + \frac{1}{T_i s}\right). \tag{10}$$

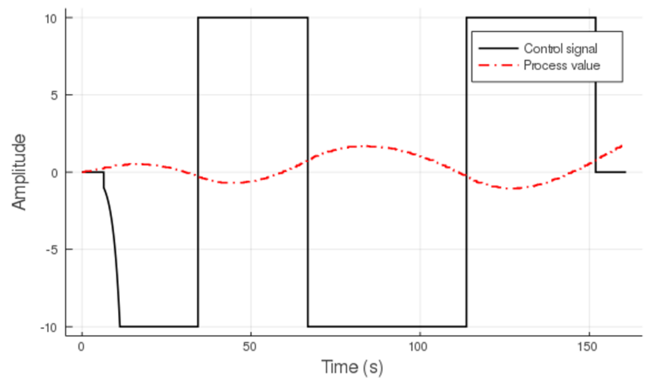


Fig. 10. The existing ABB AC 800M relay autotuner experiment on the lower tank.

TABLE IV

THE PI SETTINGS FOR THE DIFFERENT AUTOTUNERS.

PI Tuning method	K	T_i
Proposed method with AMIGO-PI	15.4	4.8
Existing autotuner	5.2	8.6

The performance for the respective PI controllers for a reference step is seen in Fig. 11 and for a load disturbance test in Fig. 12.

V. CONCLUSIONS

Through a simulation study and experiments on a real process, we have shown what a system identification method based on the work in [7] can accomplish. Through a short experiment, it is now possible to fit low-order models with time delays which match the frequency properties of the real processes with high accuracy in most cases. Furthermore, we have developed a novel method for initialising a model by combining the smooth properties of cubic splines and the fast algorithm least squares to find good initial values for process model parameter estimation from relay and chirp experiments. By implementing the method in the process automation system ABB Ability™ System 800xA it has been shown that this can be widely deployed in industrial process controllers. Furthermore, the method has been compared to the existing relay autotuner in ABB AC 800M and our method was shown to generate good results with a shorter experiment time. Through implementation and analysis this paper demonstrates a method to create the next-generation relay autotuner.

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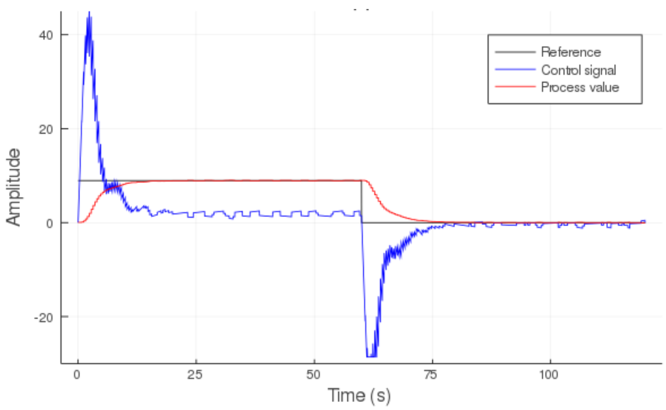
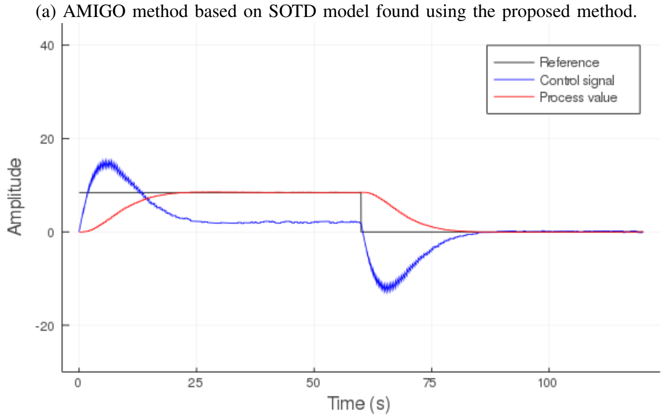


(a) AMIGO method based on SOTD model found using the proposed method.



(b) Existing AC 800M relay autotuner.

Fig. 11. A positive and a negative reference step on the upper tank process using PI controllers obtained from the the proposed method and the existing autotuner.

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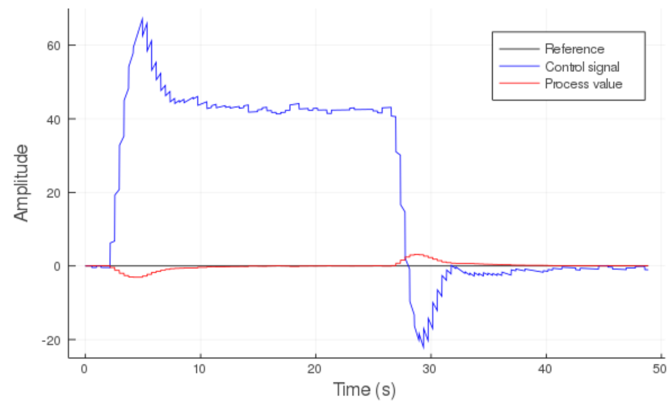
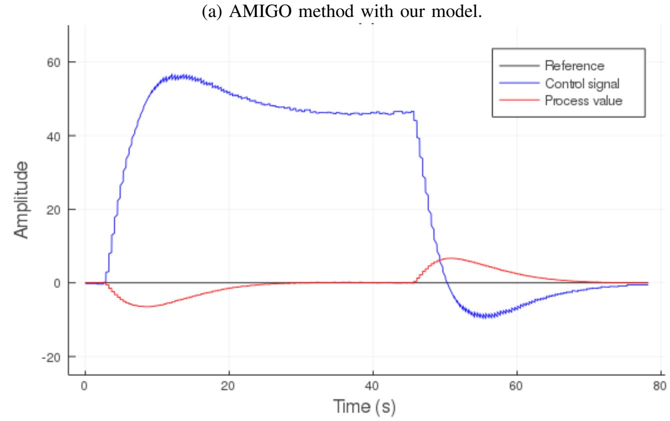


(a) AMIGO method with our model.



(b) Existing AC 800M relay autotuner.

Fig. 12. A positive and a negative load disturbance on the upper tank process using PI controllers obtained from the the proposed method and the existing autotuner.