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i-pIDtune 2.0: An Updated Interactive Tool for Integrated System Identification and PID Control

J.L. Guzmán * D.E. Rivera ** M. Berenguel * S. Dormido ***

* *Department of Informatics, University of Almería, CIESOL, ceiA3, 04120 Almería, Spain. Email:{joseluis.guzman,beren}@ual.es*
** *School for Engineering of Matter, Transport, and Energy, ASU. Tempe AZ 85287-6106 USA. Email: daniel.rivera@asu.edu*
*** *Dep. Informática y Automática, UNED. C/ Juan del Rosal, 16, 28040, Madrid, Spain. Email: sdormido@dia.uned.es*

Abstract: This paper describes *i-pIDtune 2.0*, an updated interactive software tool that integrates system identification and PID controller design. The tool supports experimental design and execution under plant-friendly conditions, high-order ARX estimation, and control-relevant model reduction leading to models that comply with IMC-PID tuning rules; these controllers can then be evaluated in simulation. All four stages are depicted simultaneously and interactively in one screen. The updated tool includes two significant new features: 1) support for "bumpless" PI-D and I-PD closed-loop simulations that provide a broader understanding of PID tuning effectiveness in practical settings and 2) extension to plants with integrating dynamics. These new features are described and illustrated with two example problems.

Keywords: PID design, control-relevant identification, interactivity, prediction-error estimation, experimental design.

1. INTRODUCTION

The basic PID controller and its variants remain the controllers of choice in many industrial applications; extending its use and effectiveness represents a worthwhile pursuit. Internal model control (IMC) is a systematic procedure for control system design based on the Q-parametrization concept, which forms the basis of many modern control design techniques (Morari and Zafiriou, 1989). The IMC design procedure applied to low-order transfer functions common to process system applications results in model-based tuning rules for PID-type controllers (Rivera et al., 1986; Rivera and Flores, 2004). A single adjustable parameter in these IMC-PID tuning rules specifies the closed-loop speed of response and directly influences the robustness of the closed-loop system.

System identification focuses on the building of dynamical models from data (Ljung, 1999) and is often considered the most challenging and time consuming step in control engineering practice. Under conditions where significant disturbances and noise are present, a rigorous system identification approach becomes an essential requirement for any controller design. However, by taking into account closed-loop performance requirements during system identification, it becomes possible to both simplify the modeling task and improve the usefulness of the model with respect to the intended application of control design; this is the essence of control-relevant identification (Rivera et al., 1992). Illustrating such synergism was the motivating philosophy behind the methodology presented in the initial version of the interactive tool *i-pIDtune*, which is described in Guzmán et al. (2012).

In recent decades, advances in information technologies have provided powerful software tools for training engineers (Dormido, 2004; Guzmán et al., 2023). Moreover, interactive software tools have been proven as particularly useful techniques with high impact on control education (Guzmán et al., 2005, 2008; Guzmán et al., 2023). Interactive tools provide a real-time connection between decisions made during the design phase and results obtained in the analysis phase of any control-related project. Prior work involving the authors resulted in *ITSIE* (Guzmán et al., 2012) and *ITCRI* (Álvarez et al., 2013). *ITSIE* focuses exclusively on open-loop system identification and *ITCRI* deals with the control-relevant identification based on prefiltered prediction-error estimation. In this paper, the goal is to describe the theory, features, and application of *i-pIDtune 2.0*, an interactive tool that integrates system identification and PID controller design. *i-pIDtune 2.0* considers the estimation of a high-order ARX model and control-relevant model reduction to obtain models consistent with the IMC-PID tuning rules. Validation criteria allow the user to verify both open-loop and closed-loop metrics. Furthermore, the tool enables the user to simulate closed-loop behavior and provides analysis tools for assessing the benefit of choosing particular tuning parameters for setpoint tracking and load disturbances. The interactive tool is coded in Sysquake, a MATLAB-like language with fast execution and excellent facilities for interactive graphics (Piguet, 2004).

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2. THEORETICAL BACKGROUND

This section summarizes the major steps of the identification methodology for IMC-PID tuning, which are included in the proposed interactive tool. These steps include experimental design and execution, high-order ARX estimation, and control-relevant model reduction leading to models that comply with the IMC-PID tuning rules.

2.1 Plant to be identified and controlled

The plant to be identified and subsequently controlled consists of a discrete-time system sampled at a value specified by the user (default value $T_s = 1$ min) and subject to noise and disturbances according to:

$$y(t) = p(q)(u(t) + n_1(t)) + (1 - \phi\, q^{-1})^{-1}\, n_2(t) \tag{1}$$

where $y(t)$ is the measured output signal, $u(t)$ is the input signal that is designed by the user, $p(q)$ is the zero-order-hold-equivalent transfer function for $p(s)$ and q is the forward-shift operator, n_1 is a white noise signal that allows to evaluate the effects of input disturbances in the data, while n_2 is a second independent white noise signal that is introduced directly to the output. The parameter ϕ allows this second added noise effect to be autocorrelated and not associated with the plant dynamics.

2.2 Experimental design and data preprocessing

The success of the identification methodology hinges on the availability of informative input/output data obtained from a sensibly designed identification experiment. The input signals used in this tool are: (i) Pseudo-Random Binary Sequences (PRBS) and (ii) multisine signals. In *i-pIDtune 2.0*, the input signal can be designed through direct parameter specification or by applying time constant-based guidelines. The input signal guidelines have been shared in prior work and thus for the sake of brevity the interested reader is referred to Guzmán et al. (2012) for a detailed description. Data preprocessing in *i-pIDtune 2.0* supports mean subtraction, differencing, subtraction of baseline values, and (through differencing the output signal) the option to remove an integrator known *a priori.*

2.3 ARX Model Estimation

i-pIDtune 2.0 uses simulated data from (1) to estimate a prediction-error (PEM) model characterized by an AutoRegressive with eXternal input (ARX) model structure

$$A(q)y(t) = B(q)u(t - n_k) + e(t) \tag{2}$$

$$y(t) = \tilde{p}(q)u(t) + \tilde{p}_e(q)e(t) \tag{3}$$

where $\tilde{p}(q)$ refers to the estimated plant model and $\tilde{p}_e(q)$ is the noise model. $A(q)$, and $B(q)$ are polynomials in q, while n_k is the system delay, represented as an integer multiple of sampling intervals.

ARX model estimation possesses two attractive properties, namely, computational simplicity and consistency. The parameters of (2) can be determined by minimizing the squared prediction error

$$\arg \min_{\tilde{p},\tilde{p}_e} \frac{1}{N}\sum_{i=1}^{N} e^2(i) = \arg\min_{\theta} \frac{1}{N}\sum_{i=1}^{N}\left[y - \varphi^T(t|\theta)\theta\right]^2 \tag{4}$$

where N represents the number of data, θ is a vector including the model parameters to be identified and $\varphi(t|\theta)$ is the model output for a given combination of the model parameters θ.

The use of Parseval's Theorem enables a frequency-domain analysis of bias effects in PEM estimation that allows deep insights into the selection of design variables for these techniques. As the number of observations $N \to \infty$, the least-squares estimation problem denoted by (4) can be written as

$$\lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} e^2(t) = \frac{1}{2\pi}\int_{-\pi}^{\pi} \Phi_e(\omega)d\omega \tag{5}$$

where $\Phi_e(\omega)$, the prediction-error power spectrum is

$$\Phi_e(\omega) = \frac{1}{|\tilde{p}_e(e^{j\omega})|^2}\left(|p(e^{j\omega}) - \tilde{p}(e^{j\omega})|^2\Phi_u(\omega) + |p(e^{j\omega})|^2\sigma_{n_1}^2 + |1 - \phi\, e^{-j\omega}|^{-2}\,\sigma_{n_2}^2\right) \tag{6}$$

Equation (6) helps explain systematic bias effects in identification, which can be readily explored in *i-pIDtune 2.0*. This includes issues relating to the spectral content in the input signal and the associated multi-objective optimization problem resulting from varying magnitudes of the noise variances $\sigma_{n_1}^2$ and $\sigma_{n_2}^2$.

In this work, the ARX model structure selection is accomplished through the use of cross-validation, where a data set other than the estimation data set is used to determine the predictive ability of a model. Because ARX estimation consists of solving a linear least squares problem (4), model estimation can be applied using a large number of model structures without incurring significant computational burden. A set of model structures is obtained by specifying a range for the orders of the model described in (2): n_a, n_b and n_k. The model structure that minimizes the loss function displays the lowest percent unexplained variance in the output.

2.4 Control-Relevant Model Reduction for IMC-PID

The application of the Internal Model Control (IMC) design procedure to establish PID tuning rules is described in detail in Morari and Zafiriou (1989) and Rivera and Flores (2004). The IMC design procedure is a two step design process that provides a suitable tradeoff between performance and robustness. In the first step a stable and causal Q-parametrized controller is obtained that is optimal with respect to norm criteria on the control error. In the second step, the controller from Step 1 is enhanced with a low-pass filter to ensure that the controller is proper. Filter parameters are used to tune the control system for robustness or a desired speed-of-response, and can be adjusted on-line once the controller is commissioned. For many simple models of interest to process control applications, the IMC controller implemented in classical feedback form leads to a PID-type controller. Table 1 contains IMC-PID tuning rules for first- and second-order models with RHP (Right Half Plane) zero (with and without integrator) that are used in *i-pIDtune 2.0*. More comprehensive tables with additional entries are found in Morari and Zafiriou (1989), Rivera and Jun (2000), and Rivera and Flores (2004).

Model	Input v_M	$\tilde{\eta} = \tilde{p}q = \tilde{p}\tilde{q}f$	K_cK	τ_I	τ_D	τ_F
$\frac{K(-\beta s+1)}{\tau s+1}$	$\frac{1}{s}$	$\frac{-\beta s+1}{\lambda s+1}$	$\frac{\tau}{\beta+\lambda}$	τ	-	-
$\frac{K(-\beta s+1)}{\tau^2 s^2+2\zeta\tau s+1}$	$\frac{1}{s}$	$\frac{(-\beta s+1)}{\lambda s+1}$	$\frac{2\zeta\tau}{\beta+\lambda}$	$2\zeta\tau$	$\frac{\tau}{2\zeta}$	-
$\frac{K(-\beta s+1)}{\tau^2 s^2+2\zeta\tau s+1}$	$\frac{1}{s}$	$\frac{(-\beta s+1)}{(\beta s+1)(\lambda s+1)}$	$\frac{2\zeta\tau}{2\beta+\lambda}$	$2\zeta\tau$	$\frac{\tau}{2\zeta}$	$\frac{\beta\lambda}{2\beta+\lambda}$
$\frac{K(-\beta s+1)}{s}$	$\frac{1}{s^2}$	$\frac{(-\beta s+1)(2\lambda+\beta)s+1}{(\lambda s+1)^2}$	$\frac{2\lambda+\beta}{(\lambda+\beta)^2}$	$2\lambda+\beta$	-	-
$\frac{K(-\beta s+1)}{s(\tau s+1)}$	$\frac{1}{s^2}$	$\frac{(-\beta s+1)((\beta+2\lambda)s+1)}{(\lambda s+1)^2}$	$\frac{\beta+2\lambda+\tau}{(\beta+\lambda)^2}$	$\beta+2\lambda+\tau$	$\frac{\tau(\beta+2\lambda)}{\beta+2\lambda+\tau}$	-
$\frac{K(-\beta s+1)}{s(\tau s+1)}$	$\frac{1}{s^2}$	$\frac{(-\beta s+1)(2(\beta+\lambda)s+1)}{(\beta s+1)(\lambda s+1)^2}$	$\frac{2(\beta+\lambda)+\tau}{2\beta^2+4\beta\lambda+\lambda^2}$	$2(\beta+\lambda)+\tau$	$\frac{2\tau(\beta+\lambda)}{2(\beta+\lambda)+\tau}$	$\frac{\beta\lambda^2}{2\beta^2+4\beta\lambda+\lambda^2}$

Table 1. IMC-PID tuning rules used in *i-pIDtune 2.0* for first and second-order plants, with and without integrator and with RHP ($\beta > 0$) zero. The general PID controller form is represented by $c(s) = K_c(1 + \frac{1}{\tau_I s} + \tau_D s)\frac{1}{(\tau_F s+1)}$.

For plants with delay or higher than second-order, a model reduction step is necessary in order to arrive at a model that conforms to the IMC-PID tuning rules. Here, we apply control-relevant model reduction to directly obtain reduced-order models without delay that conform to the IMC-PID tuning rules in Table 1. *i-pIDtune 2.0* obtains and compares tuning rules for PI, PID and PID with filter designs interactively on the same screen. The model reduction procedure is based on the control-relevant approach described in Rivera and Morari (1987). In this framework, the frequency bandwidth over which a good model fit is necessary dictated by the IMC-PID tuning rule, the value for the IMC filter parameter λ, and the setpoint-disturbance direction faced by the closed-loop system. Consider the model reduction problem arising from minimizing the 2-norm of the control error $e_c = r - y$

$$J_1 = \|e_c\|_2 = \left(\int_0^\infty \mid e_c(t) \mid^2 dt\right)^{1/2}. \tag{7}$$

The closed-loop system resulting from a feedback controller $c(s)$ designed from the estimated model $\tilde{p}$ is characterized by the nominal sensitivity operator $\tilde{\epsilon} = (1 + \tilde{p}c)^{-1}$ and complementary sensitivity operator $\tilde{\eta} = \tilde{p}c(1 + \tilde{p}c)^{-1}$. For $c(s)$ implemented on the true plant model p, the control performance deterioration caused by mismatch between plant and model is represented by

$$e_c = \frac{\tilde{\epsilon}}{1 + \tilde{\eta}\, e_m}(r - d), \tag{8}$$

where $e_m = (p - \tilde{p})\tilde{p}^{-1}$ is the multiplicative error between the true plant and the estimated model, and d represents the load disturbance. Stability of the control system is most rigorously determined by applying Nyquist Stability; a sufficient condition and computationally simpler requirement is the Small Gain Theorem

$$|\tilde{\eta}(\jmath\omega)e_m(\jmath\omega)| \leq 1 \quad \text{for all} \quad \omega. \tag{9}$$

When (9) holds, (8) can be expanded into a Taylor series which is truncated after the first term to yield

$$e_c \approx \tilde{\epsilon}(1 - \tilde{\eta}e_m)(r - d). \tag{10}$$

The previous approximation (10) is especially valid when $|\tilde{\eta}(\jmath\omega)e_m(\jmath\omega)| \ll 1$ over the bandwidth defined by $\tilde{\epsilon}(r - d)$. Substituting (10) into (7), we obtain an approximate expression for the objective function which can be written in the frequency domain using Parseval's Theorem. The statement of the control-relevant parameter estimation problem (CRPEP) is obtained by minimizing the contribution arising from model reduction error, that is,

$$\min_{\tilde{p}} \left(\frac{1}{\pi}\int_0^\infty |\tilde{\epsilon}(\jmath\omega)|^2|\tilde{\eta}(\jmath\omega)|^2|r - d|^2|e_m(\jmath\omega)|^2 d\omega\right)^{1/2}. \tag{11}$$

The CRPEP in (11) minimizes the weighted 2-norm of the *multiplicative* error. The weight function $|\tilde{\epsilon}\tilde{\eta}(r - d)|$ explicitly incorporates the desired closed-loop shape and speed of response, as well as the setpoint and disturbance characteristics of the problem.

The interactive tool includes a frequency-weighted curve-fitting algorithm presented in Rivera and Morari (1987) to solve the model-reduction problem in (11). The algorithm of Rivera and Morari (1987) relies on the iterative solution of a linear least-squares problem in the spirit of Sanathanan and Koerner (1963) that is computationally fast and facilitates interactive analysis in *i-pIDtune 2.0.*

2.5 PID control structures

As discussed previously, the interactive tool uses the ideal form for the PID controller with filter according to the following equation:

$$u(s) = K_c\left(1 + \frac{1}{\tau_I s} + \tau_D s\right)\frac{1}{\tau_F s + 1}e_c(s) \tag{12}$$

where $\tau_D = \tau_F = 0$ is considered for an PI controller, and $\tau_F = 0$ for a classical PID controller. For the PID controller, so-called "bumpless" PI-D and I-PD configurations are available using the setpoint weighting structure (Åström and Hägglund, 2006):

$$u(s) = K_c\left(e_p(s) + e_c(s)\frac{1}{\tau_I s} + e_d(s)\tau_D s\right) \tag{13}$$

with $e_p = \alpha\, r - y$ and $e_d = \gamma\, r - y$, α and γ serving as weighting factors. This allows to obtain an equivalent two-degrees-of-freedom control algorithm where the feedback controller is kept as the original PID controller but with reference filtering capabilities with the following structure:

$$F_r(s) = \frac{1 + \alpha\tau_I s + \gamma\tau_I\tau_D s^2}{1 + \tau_I s + \tau_I\tau_D s^2} \tag{14}$$

$\gamma = 0$ for the PI-D configuration, and $\gamma = \alpha = 0$ for the I-PD algorithm.

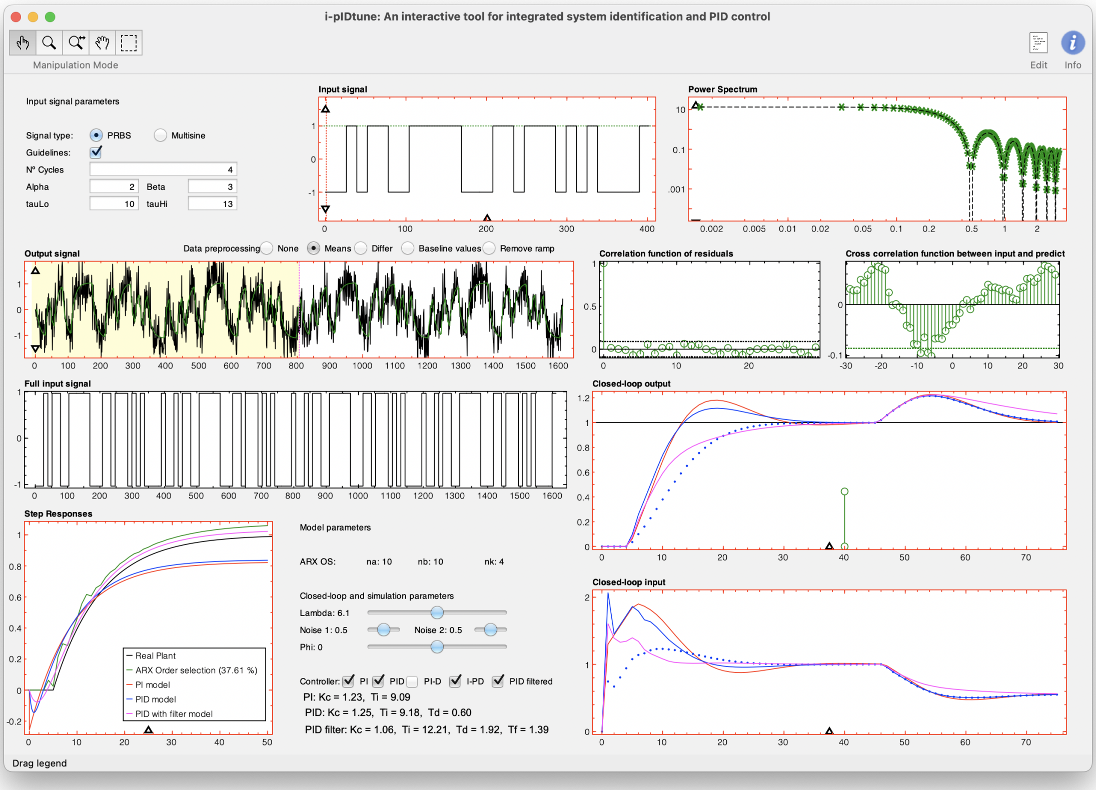

Fig. 1. Main screen of *i-pIDtune 2.0*, displaying results for the first-order with delay plant example described in Section 4.

2.6 Model validation

i-pIDtune 2.0 provides classical methods for validation such as simulation, crossvalidation, residual analysis on the prediction errors and step responses. The percent output variance on the crossvalidation data set is also reported. Furthermore, the most informative form of control-relevant validation is the closed-loop response resulting from the estimated model, which in *i-pIDtune 2.0* is contrasted simultaneously with the open-loop response.

3. INTERACTIVE TOOL DESCRIPTION

This section summarizes the main capabilities of the interactive tool. To test the interactive features, the reader is cordially invited to download the tool at `https://arm.ual.es/i-pidtune/`. The main graphical interface is shown in Fig. 1, and has been designed following the main steps in a control-relevant identification, as follows:

- *Input signal definition.* There is a section called Input signal parameters, located in the upper left corner, where the input signal type (PRBS or multisine) can be selected. Furthermore, a checkbox called Guidelines is available to determine the signal design by following the guidelines given in Guzmán et al. (2012) or selecting the signal parameters directly. More information on input design options can be found in Guzmán et al. (2012). At the right of these parameters, there are two graphics, namely Input signal, which shows one cycle of the input signal, and Power Spectrum or AutoCorrelation (depending on the option chosen in the menu Options), which shows the input signal correlation or the input signal power spectrum, respectively. In the graph Full input signal located in the left of the central part of the screen, the full input signal is presented.
- *Data preprocessing and model estimation.* Above the Output signal graph, the different data preprocessing options are available, namely, mean subtraction, differencing, substraction of baseline values, and remove ramp or integrator. On the other hand, in the section called Model parameters, located in the bottom central part of the screen, the parameters n_a, n_b and n_k for the high-order ARX model, ARX OS, are shown.
- *Closed-loop specification.* Below the Model parameters section, a slider called Lambda allows us to modify the λ for the IMC filter time constant used by the IMC-PID tuning rules presented in Table 1. Moreover, the noise sources in the data and the output, n_1 and n_2, can be changed using the sliders called Noise 1 and Noise 2, respectively. On the other hand, five different checkboxes are available to select among the desired control structure, PI, PID, PI-D, I-PD or PID with filter. Once the control structure is selected, the corresponding controller parameters are depicted.
- *Model validation.* The Output signal graphic includes a vertical line which allows interactively defining the estimation (yellow area) and validation data (white area) sets. This figure also shows the 'simulated' real data (in black) together with the response of the high-order ARX model (in green). The model validation

results are presented in two different graphics: Correlation function of residuals and Step Responses. In the case of the Step Responses graph, four different responses can be shown, for the high-order ARX model, for the PI model (control-relevant model for PI controller tuning), for the PID model (control-relevant model for PID controller tuning) and for the PID with filter model (control-relevant model for PID controller with filter tuning). For the case of the high-order ARX model, its goodness of fit in % is displayed, and the confidence intervals can be shown by using the corresponding option in the menu Parameters.

- *Closed-loop response.* The closed-loop responses for the selected control algorithms are shown in the figures Closed-loop output and Closed-loop input for the process output and the control signal, respectively.

4. ILLUSTRATIVE EXAMPLES

Two examples are presented to show the operation and expanded functionality of *i-pIDtune 2.0*. In the first example, a first-order with deadtime plant is considered. The system is represented by the transfer function:

$$p(s) = \frac{e^{-5s}}{(10s+1)} \tag{15}$$

with a default sample time of $T_s = 1$ min. The main aim of this example is to analyze the control-relevant method and to compare the resulting PID controller tuning. Results are shown in Fig. 1. A PRBS input signal is used for identification, with parameters: $m = 4$ (number of cycles), $\alpha_s = 2$, (factor representing the closed-loop speed of response), $\beta_s = 3$ (factor representing the settling time of the process), $\tau^L_{\text{dom}} = 10$ (low estimate of τ_{dom}) and $\tau^H_{\text{dom}} = 13$ (high estimate of τ_{dom}). For more information about these parameters, see Guzmán et al. (2012).

A high-order ARX model, ARX-[10 10 4], is obtained from this identification signal. Its open loop response is shown in the Step Responses graph (ARX-OS), at the lower left-hand side of the tool, together with the response of three control-relevant models for PI, PID, and PID with filter. The validation criteria indicate the modest (37.6%) fit in the ARX model, due to the noise signals n_1 and n_2, is the result of ARX model estimation being a trade-off between the fit to the noise model and the fit to the transfer function. However, despite a modest fit of the ARX model from an "open-loop" point of view, this result is a very important contribution for control-relevant design. The ARX model enables cleaning the noisy data and estimating the main process dynamics, which are then used to estimate the reduced control-relevant models. These results would be very difficult to obtain from conventional methods based on process reaction curve and relay tests.

Regarding the closed-loop parameters, the parameter λ of the IMC controller is lowered from the default value of 10 to $\lambda = 6.1$, thus implying the desire for a faster speed of response. The open-loop response of the resulting reduced models are shown in Step Responses graph. It can be observed how the model for PID controller with filter is the one obtaining the closest response to the high-order ARX model. The inputs and outputs of the resulting feedback system are shown in Closed-loop input and Closed-loop output graphs, respectively. Notice the poor performance of the closed-loop system for the PI controller (red solid line) and PID controller (blue solid line), with a large overshoots of approximately 20% of the setpoint change magnitude. This fact is due to the bad fit of the open loop reduced models for these controllers. From the Step Responses graph, it is possible to note how there is a substantial mismatch in the static gain between the PI model and PID model and the high-order ARX model, ARX-OS. Recall that the proposed control-relevant model reduction method tries to estimate a model without delay corresponding to the model structures described in Table 1. The PID with filter model has a much closer "control-relevant" fit, enabling a faster bandwidth and hence its closed-loop response (for setpoint tracking) is much better than for PI and PID.

Evaluating the I-PD response yields some interesting insights. The setpoint tracking response is overdamped and improved substantially compared to PID, mimicking that of the PID with filter controller. Disturbance rejection (which remains unchanged regardless of PID, PI-D, or I-PD) is faster than for the PID with filter controller. The two-degree-of-freedom response from the I-PD controller demonstrates added versatility that can be obtained from IMC-tuned PID parameters. When the closed-loop specification is relaxed (e.g., $\lambda = 20$; not shown), the control-relevant approximate models for the PI, PID, and PID with filter cases are very similar, and practically identical (although de-tuned) closed-loop responses are obtained for the three cases.

The second example is an integrating system with delay

$$p(s) = \frac{e^{-5s}}{s}. \tag{16}$$

The *i-pIDtune 2.0* window is shown in Fig. 2. Again a PRBS input signal is used, with parameters: $m = 6$, $\alpha_s = 2$, $\beta_s = 3$, $\tau^L_{\text{dom}} = 3$ and $\tau^H_{\text{dom}} = 5$. Here the Remove Ramp option is used in the identification, which recognizes the presence of integrating dynamics in the data; a similar ARX model fit to the data (36.2%) is obtained. For $\lambda = 10$, all three reduced models (PI model, PID model and PID with filter model) approximate the delay with a RHP zero, with differences manifesting themselves in the closed-loop responses (seen in Fig. 2); the PI model being the most inferior. As with the first example, the I-PD response substantially improves the PID response and could be argued to be better than the PID with filter case.

5. CONCLUSIONS

This paper describes an interactive tool integrating system identification and IMC-PID controller design. By using *i-pIDtune 2.0* it is possible to achieve interactively such synergism, being that the motivating philosophy behind the methodology described in this paper. The tool provides different functionality modes which make possible to use its capabilities for students and engineers with a small learning curve. The tool is freely available from `https://arm.ual.es/i-pidtune/`. The interactive tool allows the student to analyze a straightforward control-relevant procedure and to compare the closed-loop results from different reduced models.

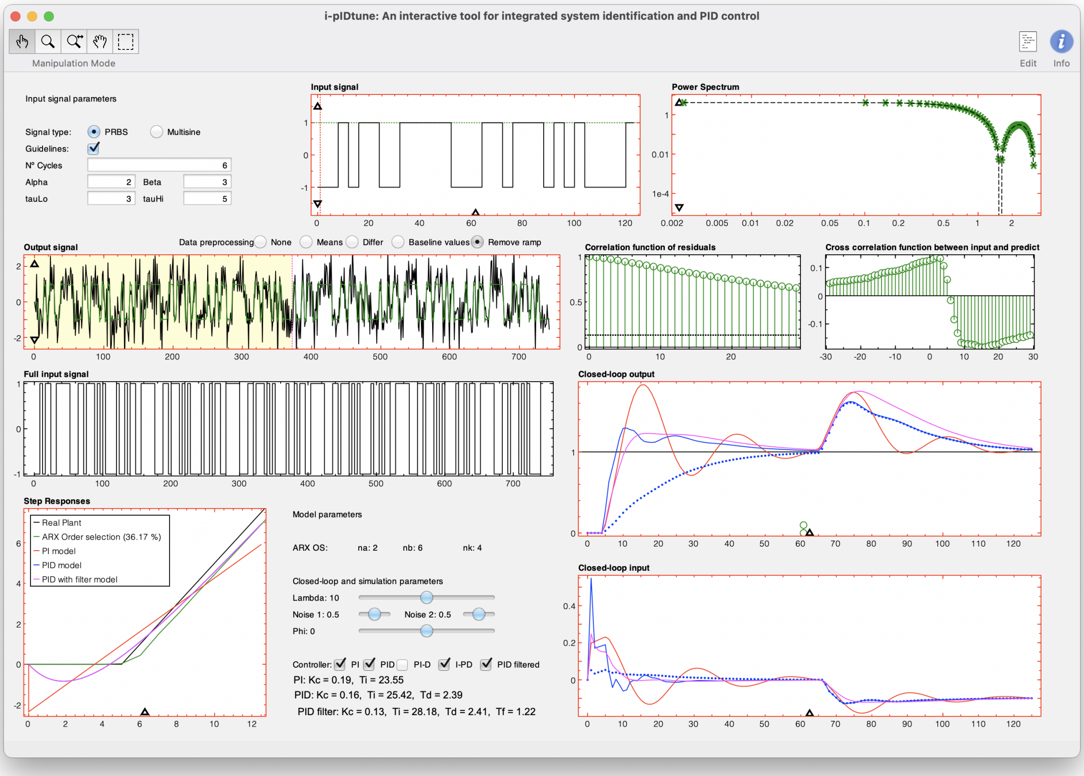

Fig. 2. Results for the second example (a delayed plant with integrator) described in Section 4.

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