# *i-pIDtune*: An interactive tool for integrated system identification and PID control

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

* *Dep. de Lenguajes y Computación, Universidad de Almería, 04120 Almería, Spain. Email:{joguzman,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*, an 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 the IMC-PID tuning rules. All these stages are depicted simultaneously and interactively in one screen. Thus, *i-pIDtune* allows to display both open- and closed-loop responses of the estimated models and important control-relevant validation criteria, what enables the user to readily assess how design variable choices, control performance requirements and model error can impact the achievable closed-loop performance from a restricted complexity model estimated under noisy conditions.

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

## 1. INTRODUCTION

Despite significant strides in the development of advanced control schemes over the past two decades, the basic PID controller and its variants remain the controllers of choice in many industrial applications. As many as 95% of all control loops in the process industries employ a PID-type algorithm (Åström and Hägglund, 2006). While the computational ability of modern-day distributed control systems continues to increase, PID controllers remain a favorite because of their structural simplicity, reliability, and favorable ratio between performance and cost. Beyond these benefits, PID control offers simplified dynamic modeling, lower user-skill requirements, and reduced development effort, which are issues of substantial importance to engineering practice. 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. 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 (Rivera et al., 1986), (Rivera and Flores, 2004).

By integrating system identification and IMC-PID controller design, high-performance controllers are simpler to obtain than if the two tasks are conducted independently. Achieving such synergism is the motivating philosophy behind the methodology included in the interactive tool which is described in this article. PID controller tuning starting from input-output data is a well-understood problem when the plant is free of disturbances and high noise. PID tuning from process reaction curves and relay tuning (Åström and Hägglund, 2006), (Atherton, 1999), (O'Dwyer, 2003) are techniques that work well in low noise circumstances. However, many PID control problems of practical industrial significance do not fall into this category, and system identification for PID control include important challenges in these cases.

System identification focuses on the building of dynamical models from data (Ljung, 1999). It is often considered the most challenging and time consuming step in control engineering practice and thus represents an important component in the professional training of any control engineer; to this end, flexible and simple-to-use software tools are essential. Classical system identification is focused on satisfying "open-loop" criteria that may lead to high-order models that are not directly suitable for control design. However, by taking into account controller 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; van den Hof and Callafon, 2003).

In recent years, advances in information technologies have provided powerful software tools for training engineers (Dormido, 2004; Guzmán et al., 2009). Moreover, inter-

* This work has been partially funded by the following projects: DPI2007-61068, DPI2010-21589-C05-04 and DPI2011-27818-C02-01 (financed by the Spanish Ministry of Science and Innovation and ERDF funds).

active software tools have been proven as particularly useful techniques with high impact on control education (Guzmán et al., 2005, 2008). 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 has resulted in *ITSIE*, an **I**nteractive software **T**ool for **S**ystem **I**dentification **E**ducation (Guzmán et al., 2009) and *ITCRI*, and **I**nteractive **T**ool for **C**ontrol **R**elevant **I**dentification. *ITSIE* focuses exclusively on open-loop system identification and *ITCRI* deals with the control-relevant identification based on prefiltered prediction-error estimation procedures. The main objective of this paper is to describe the theory, features, and application of *i-pIDtune*, an interactive tool that integrates system identification and PID controller design. This tool provides an interactive version of a preliminary tool presented in (Flores and Rivera, 2000), which was developed for Matlab. *i-pIDtune* considers the estimation of a high-order ARX model and control-relevant model reduction to obtain models consistent with the Internal Model Control (IMC) PID tuning rules. Validation criteria allow the user or student to check open-loop and closed-loop criteria, for instance, how open-loop error in the model translates into adequate or poor closed-loop behavior. Furthermore, the tools allows the user to simulate closed-loop behavior and provides analysis tools for assessing the benefits 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).

## 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 within the interactive tool, 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:

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

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 stationary white noise that allows to evaluate the effects of autocorrelated disturbances in the data and $n_2$ is another stationary white noise that is introduced directly to the output signal.

### *2.2 Experimental design and data preprocessing*

The success of the identification methodology hinges on the availability of an informative input/output data set obtained from a sensibly designed identification experiment. The input signals used in this work are: (i) Pseudo-Random Binary Sequences (PRBS) and (ii) multisine signals. In *i-pIDtune*, the input signal can be designed through direct parameter specification or by applying time constant-based guidelines. The input signal guidelines and parameters are shared with the previous works, and thus, for the sake of brevity the interested reader is referred to (Guzmán et al., 2009) for a detailed description. Data preprocessing in *i-pIDtune* supports mean subtraction, differencing, and substraction of baseline values.

### *2.3 ARX Model Estimation*

The interactive tool uses 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, $\theta$ 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 $\theta$.

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 $N \rightarrow \infty$, 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

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

Equation (6) helps explain systematic bias effects in identification, which can be readily explored in *i-pIDtune*. 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. In cross-validation, 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), repeated 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) - (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. More comprehensive tables with additional entries are found in (Morari and Zafiriou, 1989) - (Rivera and Flores, 2004) and (Rivera and Jun, 2000).

| Model | $KK_c$ | $\tau_I$ | $\tau_D$ | $\tau_F$ |
|---|---|---|---|---|
| $\frac{K(-\beta s+1)}{\tau s+1}$ | $\frac{\tau}{\beta+\lambda}$ | $\tau$ | - | - |
| $\frac{K(-\beta s+1)}{\tau^2 s^2+2\zeta\tau s+1}$ | $\frac{2\zeta\tau}{\beta+\tau}$ | $2\zeta\tau$ | $\frac{\tau}{2\zeta}$ | - |
| $\frac{K(-\beta s+1)}{\tau^2 s^2+2\zeta\tau s+1}$ | $\frac{2\zeta\tau}{2\beta+\lambda}$ | $2\zeta\tau$ | $\frac{\tau}{2\zeta}$ | $\frac{\beta\lambda}{2\beta+\lambda}$ |

Table 1. IMC-PID tuning rules for first and second-order plants without integrator and with nonminimum phase zero $\beta > 0$. 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* allows to obtain and to compare these three 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 $\lambda$, 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 $e_c = r - y$

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

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. Nominal closed-loop stability applying $c$ on $\tilde{p}$ does not guarantee stability with regards to $p$. Stability of the control system is most rigorously determined by applying the Nyquist Stability Criterion on $\tilde{\eta}\ e_m$. 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 written in the frequency domain using Parseval's Theorem has the form

$$\|e_c\|_2 \approx \left(\frac{1}{\pi}\int_0^\infty |\tilde{\epsilon}|^2|1 - \tilde{\eta}e_m|^2|r - d|^2 d\omega\right)^{1/2} \tag{11}$$

$$\leq \left(\frac{1}{\pi}\int_0^\infty |\tilde{\epsilon}|^2|r - d|^2 d\omega\right)^{1/2} + \left(\frac{1}{\pi}\int_0^\infty |\tilde{\epsilon}|^2|\tilde{\eta}e_m|^2|r - d|^2 d\omega\right)^{1/2}. \tag{12}$$

Note that (12) has one term based on the nominal properties of the closed-loop response and a second term based on the reduction error $e_m$. The statement of the control-relevant parameter estimation problem is obtained by minimizing the contribution arising from model reduction error in the second term, that is,

$$\min_{\tilde{p}} \left(\frac{1}{\pi}\int_0^\infty |\tilde{\epsilon}(\jmath\omega)|^2|\tilde{\eta}(\jmath\omega)|^2|r - d|^2|e_m(\jmath\omega)|^2 d\omega\right)^{1/2}. \tag{13}$$

The control-relevant parameter estimation problem (13) minimizes the weighted 2-norm of the *multiplicative* error, as opposed to the unweighted 2-norm *additive* error ($e_a = p - \tilde{p}$) that is commonly examined in the control literature. 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 (13). The algorithm of (Rivera and Morari, 1987), which relies on the iterative solution of a linear least-squares problem in the spirit of (Sanathanan and Koerner, 1963), is computationally fast, what allows interactive analysis in *i-pIDtune*.

### *2.5 Model validation*

*i-pIDtune* 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* is contrasted simultaneously with the open-loop response.

## 3. INTERACTIVE TOOL DESCRIPTION

This section is devoted to describe the mean features of the interactive tool. However, it is important to mention that interactivity which is the main feature, cannot be noticed in a written text. Thus, the reader is cordially invited to download the tool at `http://aer.ual.es/i-pidtune/` (see Fig. 1) and personally experience its interactivy.

The graphical distribution has been designed according to the most important steps in a control-relevant identification. It is described as follows (see Fig. 1):

- *Input signal definition.* In the main screen, at the top left corner, there is a section called Input signal parameters. Here, the user can choose the type of the input signal (PRBS or multisine) and by means of the checkbox called Guidelines to decide between specifying the input signal directly or following the guidelines given in (Guzmán et al., 2009). For instance, if the PRBS is selected without activating the checkbox Guidelines, a text edit and two sliders appear to modify the number of cycles (N Cycles), the number of registers (N Reg), and the switching time (Tsw). At the top center and top rigth corner, there are two graphics namely Input signal and Power Spectrum or AutoCorrelation depending on the chosen option. The graph in the center, Input signal, shows one cycle of the input signal, the graph below represents the input signal correlation or the input signal power spectrum depending on the chosen option in the radio buttons at the top right of the graph. The input signal can be modified dragging on both graphics too. Once an input signal has been configured, the final input signal is shown in Full input signal graph, located at the left of the central part of the main screen.
- *Model estimation.* In the bottom central part of the screen, there is a section called Model parameters, where the resulting parameters $n_a$, $n_b$ and $n_k$ for the high-order ARX model, ARX OS, are shown.
- *Closed-loop specification.* In the section Closed loop and simulation parameters, below the Model parameters section, the parameter $\lambda$ for the IMC filter time constant, which is used by the IMC-PID tuning rules presented in Table 1, is specified through a slider called Lambda. Below this slider, other two sliders called Noise 1 and Noise 2 determine the level of noise in the data, $n_1$, and in the output signal, $n_2$, respectively. Furthermore, the desired resulting controllers PI, PID or PID with filter can be selected from three checkboxes appearing in these same area of the tool. Once the type of the controller is selected, the corresponding control-relevant model (see Table 1) is identified and the associated controller parameters are calculated and shown below these checkboxes.
- *Model validation.* The magenta-colored vertical line of the Output signal graphic is interactively used to define the estimation (yellow area) and validation data (white area) sets. The validation data is used for crossvalidation purposes. Model validation results are displayed in other two different graphics: Step Responses and Correlation function of residuals. The Step Responses graph, which is located at the lower left-hand side of the tool, shows the step responses for the following models: (i) ARX-OS: an ARX high-order model, green line, (ii) PI model: control-relevant model for PI controller tuning, red line, (iii) PID model: control-relevant model for PID controller tuning, blue line, and,(iv) PID with filter model: control-relevant model for PI controller with filter tuning, magenta line. For high-order ARX model, its goodness of fit in % is also showed. Confidence intervals can be also shown in this graphic activating this option from the Parameters menu for the high-order ARX model.
- *Closed-loop response.* At the lower right corner of the tool, there are two graphs that show the closed-loop response of the resulting feedback control system. These graphs are called Closed-loop output where the output of the closed loop is showed and Closed-loop input, where the output of the calculated IMC controller is displayed.

## 4. ILLUSTRATIVE EXAMPLE

In this example, a simulated fifth-order system is considered. The system is represented by the transfer function:

$$p(s) = \frac{1}{(s+1)^5} \tag{14}$$

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 designs. Results are shown in Fig. 1 and 2. A PRBS input signal is used for identification, with parameters: $m = 8$ (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), $\tau^L_{\text{dom}} = 3$ (low estimate of $\tau_{\text{dom}}$) and $\tau^H_{\text{dom}} = 5$ (high estimate of $\tau_{\text{dom}}$). For more information about these parameters see (Guzmán et al., 2009). Moreover, the noise on the output signal, $n_2(t)$ in Eq. (1), is augmented to a value of 5.3, whereas the noise on the disturbance ($n_1(t)$ in Eq. (1)), is set to 1.5.

A high-order ARX model, ARX-[6 4 1], 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 indicates the poor fit of the ARX model. This is due to the high value of the noise signals $n_1$ and $n_2$, since ARX model estimation involves a tradeoff between


Fig. 1. Main screen of *i-pIDtune*, displaying results for the illustrative example explained in Section 4.

the fit to the noise model and the fit to the transfer function. However, despite this poor fit of the ARX model from an identification point of view, this result is a very important contribution for control-relevant design. Notice the highly noisy data which is being evaluated (see the graphic Output Signal). The ARX model allows to clean that noisy data and obtain the main process dynamics, which is then used to estimate the reduced control-relevant models. These identification procedure would be very difficult to perform from conventional methods based on process reaction curve and relay tests.

Regarding the closed-loop parameters, the parameter $\lambda$ of the IMC controller is set to $\lambda = 2.4$. 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 a closer 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), with a large overshoot of 55 % of the setpoint change magnitude. This fact is due to the bad fit of the open loop model for this controller. 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 the high-order ARX model, ARX-OS. This mismatch is even higher when the resulting PI model is compared with the real system (black solid line). Furthermore, the PI model presents an important non-minimum phase behavior, what clearly reduced the bandwidth of the closed-loop system. Remember that the proposed control-relevant model reduction method tries to estimate a model without delay, for the model structures described in Table 1. In case of PID and PID with filter, the closed-loop responses are much better than for PI. The reason is that the resulting control-relevant models for these cases are much better, as can be observed in Step Responses graph. Notice how both models, PID model and PID with filter model have a similar response, having the PID with filter model a better static gain estimation. These models, PID model and PID with filter model, present a better estimation in the non-minimum phase zero than the PI model, what allows to reach a higher closed-loop bandwidth. This can be clearly observed in the closed-loop responses, where for the same required closed-loop specification, $\lambda$, the PID and the PID with filter controllers show a much better performance.

When the closed-loop specification is relaxed, for instance for $\lambda = 10$, the estimation for the three models, PI model, PID model and PID with filter model provides very similar responses and practically the same closed-loop responses are obtained for the three cases, such as shown in Fig. 2.

## 5. CONCLUSIONS

This paper describes an interactive tool integrating system identification and IMC-PID controller design. By using *i-pIDtune* 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 available for free from `http://aer.ual.es/i-pidtune/`. The interactive tool allows the student to analyze a straightforward control-relevant procedure and to compare the closed-loop results

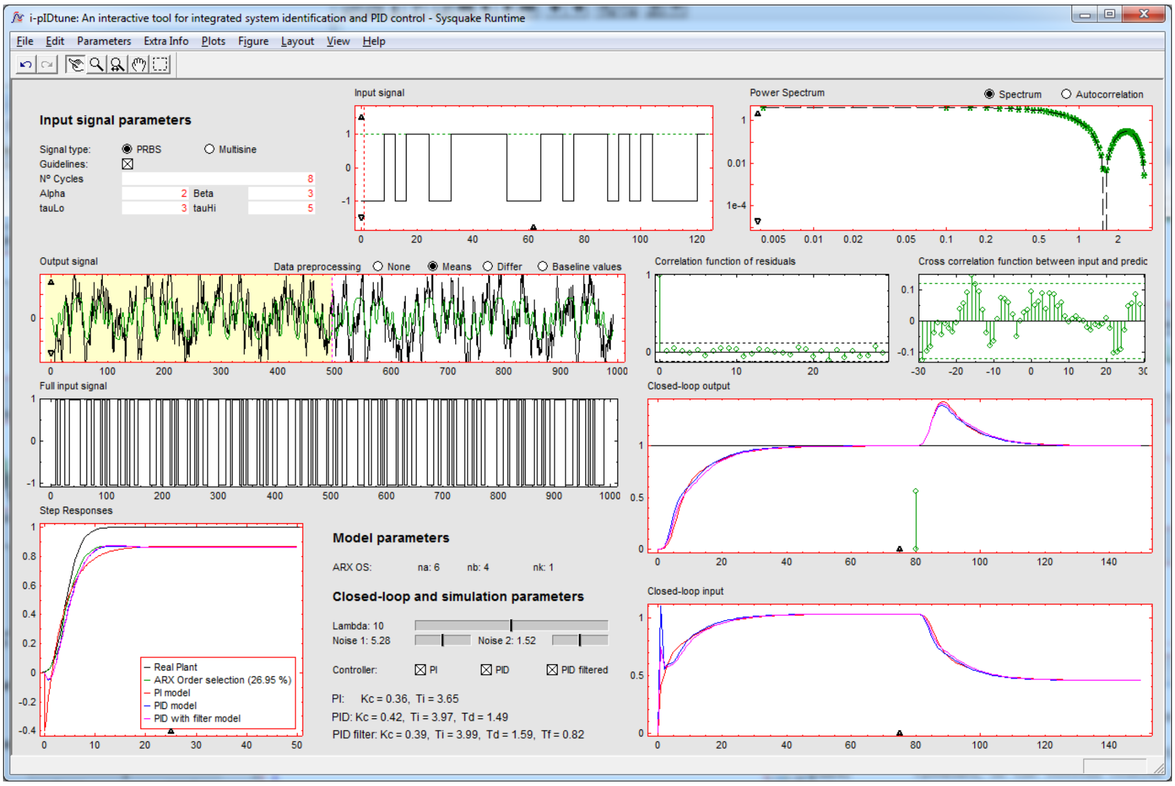


Fig. 2. Results for the illustrative example explained in Section 4.

from different reduced models. Future work will be oriented to include other techniques for the identification phase (such as the step response analysis by the method of areas or similar ones) and for the PID tuning stage, where comparisons among different methods could be interactively performed with the tool.

## REFERENCES

Åström, K. and Hägglund, T. (2006). *Advanced PID Control*. Instrument Society of America, Research Triangle Park, North Carolina.

Atherton, D. (1999). PID controller tuning. *Computing and Control Engineering Journal*, 10(2), 44–50.

Dormido, S. (2004). Control learning: present and future. *Annual Reviews in Control*, 28(1), 115–136.

Flores, M.E. and Rivera, D.E. (2000). pIDtune: A Graphical Package for Integrated System Identification and PID Controller Design. In $12^{th}$ *IFAC Symposium on System Identification (SYSID 2000)*, 681–686. Santa Barbara, CA.

Guzmán, J.L., Åström, K.J., Dormido, S., Hägglund, T., Berenguel, M., and Piguet, Y. (2008). Interactive learning modules for PID control. *IEEE Control System Magazine*, 28(5), 118–134. Available: http://aer.ual.es/ilm/.

Guzmán, J.L., Berenguel, M., and Dormido, S. (2005). Interactive teaching of constrained generalized predictive control. *IEEE Control Systems Magazine*, 25(2), 52–66. Available: http://aer.ual.es/siso-gpcit/.

Guzmán, J.L., Rivera, D.E., Dormido, S., and Berenguel, M. (2009). ITSIE: An interactive software tool for system identification education. In *15th IFAC Symposium on System Identification*, `http://aer.ual.es/ITSIE/`. St. Malo, France.

Ljung, L. (1999). *System Identification: Theory for the User*. Prentice-Hall, New Jersey, 2nd edition.

Morari, M. and Zafiriou, E. (1989). *Robust Process Control*. Prentice-Hall, New Jersey.

O'Dwyer, A. (2003). *Handbook of PI and PID controller tuning rules*. World Scientific Publishing, Singapore.

Piguet, Y. (2004). *SysQuake 3 User Manual*. Calerga S'arl, Lausanne (Switzerland).

Rivera, D.E., Polland, J.F., and García, C.E. (1992). Control-relevant prefiltering: A systematic design approach and case study. *IEEE Transactions on Automatic Control*, 37(7), 964–974.

Rivera, D. and Flores, M. (2004). Internal Model Control. In H. Unbehauen (ed.), *6.43. Control Systems, Robotics and Automation, Encyclopedia of Life Support Systems (EOLSS)*. Eolss Publishers, Oxford, UK.

Rivera, D. and Jun, K. (2000). An integrated identification and control design methodology for multivariable process system applications. *IEEE Control Systems Magazine*, 20, 25–37.

Rivera, D. and Morari, M. (1987). Control-Relevant Model Reduction Problems for SISO $H_2$, $H_\infty$, and $\mu$ Controller Synthesis. *Int. J. Control*, 46, 505–527.

Rivera, D., Morari, M., and Skogestad, S. (1986). Internal Model Control 4. PID Controller Design. *Ind. Eng. Chem. Process Des. Dev.*, 25, 252–265.

Sanathanan, C.K. and Koerner, J. (1963). Transfer function synthesis as a ratio of two complex polynomials. *IEEE Trans. on Automatic Control*, 9, 56–58.

van den Hof, P.M.J. and Callafon, R.A. (2003). *Identification for Control*, volume V of *Control Systems, Robotics and Automation. Encyclopedia of Life Support Systems (EOLSS), Developed under the auspices of the UNESCO*. Eolss Publishers, Oxford, UK.