ITCLI: An Interactive Tool for Closed-Loop Identification

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Abstract: This paper describes *ITCLI*, an interactive software tool for understanding SISO closed-loop identification using prediction-error techniques. The tool enables an interactive evaluation regarding how bias and variance effects play a role in identification under closed-loop circumstances. The role of external signal design, choice of model structure, controller tuning during identification testing, and signal injection points (at either the manipulated variable or the setpoint) all under the presence of autocorrelated disturbances are considered. The software is developed using Sysquake and is provided as a stand-alone executable version in multiple operating environments.

Keywords: Closed-loop identification, interactivity, direct prediction-error estimation, control education

1. INTRODUCTION

Closed-loop identification is an important practical problem in system identification (Wellstead, 1977; Forssell and Ljung, 1999; Ljung, 1999). In many practical situations, it is not possible to identify a system in the open-loop; hence closed-loop identification becomes a necessity. A fundamental challenge presented by closed-loop identification in contrast to open-loop is that there exists correlation between the manipulated variable and the disturbance as a result of the action of a closed-loop system. Prior research in the area establishes that despite the correlation between these signals, it is possible to consistently estimate both the plant and disturbance models in the absence of any external excitation (outside of what may be naturally present in the closed-loop system) provided there is *a priori* information regarding the model structure. In practice this is often not the case, so it is important to establish how appropriate experimental design and selection of other design variables in the identification process can facilitate the closed-loop identification problem. This includes the use, excitation, and location of an experimental signal, as well as sensible tuning of the closed-loop system. The purpose, then, of *ITCLI*, an **I**nteractive Software **T**ool for **C**losed **L**oop System **I**dentification is to examine these various design variables in closed-loop system identification in an accessible and informative software environment.

In recent years, advances in information technologies have provided powerful software tools for training engineers (Dormido, 2004; Guzmán et al., 2009). Moreover, interactive 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, 2012b) and *ITCRI* an **I**nteractive **T**ool for **C**ontrol **R**elevant **I**dentification (Álvarez et al., 2011; Álvarez et al., 2013). *ITSIE* focuses exclusively on open-loop system identification, while *ITCRI* deals with the control-relevant identification based on open-loop prefiltered prediction-error estimation procedures. Our team has also developed *i-pIDtune*, an interactive tool that integrates system identification and PID controller design (Guzmán et al., 2012a). *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. All these interactive tools are coded in Sysquake, a MATLAB-like language with fast execution and excellent facilities for interactive graphics (Piguet, 2004).

The paper is organized as follows. First, a brief description of theoretical background relating to the tool is presented in Section 2. Issues in closed-loop identification, with emphasis on how bias is influenced by the choice of design variables in closed-loop id is discussed in Section 3. Section 4 describes the functionality of the tool, with illustrative examples presented in Section 5. Finally, Section 6 presents the main conclusions and future research work.

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2. THEORETICAL BACKGROUND

This section summarizes the major steps of the methodology for closed-loop identification, which are included in the proposed interactive tool. These steps include experimental design and execution and prediction-error parameter estimation under closed-loop conditions.

2.1 Plant to be identified and controlled

The plant to be identified consists of a fifth-order system according to

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

The model per (1) is sampled at a value specified by the user (default value $T = 1$ min) and is subject to noise and disturbances according to

$$y(t) = p(q)(u(t) + n_1(t)) + n_2(t) \tag{2}$$
$$= p(q)u(t) + \nu(t) \tag{3}$$

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. The total disturbance signal is represented as $\nu(t) = P(q)n_1(t) + n_2(t)$.

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 *ITCLI*, 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. (2012b) for a detailed description. Data preprocessing in *ITCLI* supports mean subtraction, differencing, and subtraction of baseline values.

2.3 Prediction error model estimation

The interactive tool uses data from (2) to estimate a prediction-error (PEM) model. The general family of prediction-error models corresponds to

$$A(q)y(t) = \frac{B(q)}{F(q)}u(t-nk) + \frac{C(q)}{D(q)}e(t) \tag{4}$$
$$y(t) = \tilde{p}(q)u(t) + \tilde{p}_e(q)e(t) \tag{5}$$

where $\tilde{p}(q)$ refers to the estimated plant model and $\tilde{p}_e(q)$ is the noise model, and $A(q)$ through $F(q)$ are polynomials in q

$$A(q) = 1 + a_1q^{-1} + \ldots + a_{n_a}q^{-n_a}$$
$$B(q) = b_1 + b_2q^{-1} + \ldots + b_{n_b}q^{-n_b+1}$$
$$C(q) = 1 + c_1q^{-1} + \ldots + c_{n_c}q^{-n_c}$$
$$D(q) = 1 + d_1q^{-1} + \ldots + d_{n_d}q^{-n_d}$$
$$F(q) = 1 + f_1q^{-1} + \ldots + f_{n_f}q^{-n_f}$$

n_k is the system delay, represented as an integer multiple of sampling intervals. The five most popular PEM models are evaluated in *ITCLI*, with FIR belonging as a subset of ARX models. The tool also includes PEM estimation of state-space models.

PEM model estimation possesses two attractive properties, namely, robust computation using regression approaches (linear and nonlinear) and consistency. The parameters of (5) can be determined by minimizing the squared prediction error

$$\arg \min_{\tilde{p},\tilde{p}_e} \frac{1}{N}\sum_{i=1}^{N} e^2(i) = \arg\min_{\theta} \frac{1}{N}\sum_{i=1}^{N} \left[y - \varphi^T(t|\theta)\theta\right]^2 \tag{6}$$

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.

2.4 Closed-loop control

Closed-loop control implemented in *ITCLI* stems from the application of the IMC design procedure to restricted complexity approximations for the plant according to (1), using the control-relevant identification procedure implemented in *i-pIDtune*. The resulting controllers conforming to PI, PID, and PID with filter structures (summarized in Table 1) have an adjustable parameter λ that corresponds to roughly the closed-loop speed-of-response.

Model	KK_c	τ_I	τ_D	τ_F
$\frac{K(-\beta s+1)}{\tau s+1}$	$\frac{\tau}{\beta+\lambda}$	τ	-	-
$\frac{K(-\beta s+1)}{\tau^2s^2+2\zeta\tau s+1}$	$\frac{2\zeta\tau}{\beta+\tau}$	$2\zeta\tau$	$\frac{\tau}{2\zeta}$	-
$\frac{K(-\beta s+1)}{\tau^2s^2+2\zeta\tau s+1}$	$\frac{2\zeta\tau}{2\beta+\lambda}$	$2\zeta\tau$	$\frac{\tau}{2\zeta}$	$\frac{\beta\lambda}{2\beta+\lambda}$

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 $c(s) = K_c(1 + \frac{1}{\tau_I s} + \tau_D s)\frac{1}{(\tau_F s+1)}$.

3. UNDERSTANDING CLOSED-LOOP IDENTIFICATION

Error in system identification is a consequence of bias and variance effects. Bias refers to systematic errors that occur in identification as a result of factors such as the choice of model structure, the magnitude of the input signal, and the mode of operation (open or closed loop). These errors persist even if an infinite number of data points were collected during the identification. Variance effects are a consequence of randomness in the data, and this can normally be reduced through increasing the number of data points collected, increasing power for certain inputs, and model structure. In the closed-loop identification setting, controller tuning will play a role as well.

3.1 Problems caused by bias

Bias expressions can be very helpful in terms of relating design variables in identification to the performance objective of the parameter estimation problem. Bias expressions for open-loop least-squares prediction-error identification are well known, based on the seminal work by Ljung (1999). Consider a linear plant with disturbance represented by the equation (2). $u(t)$ is a quasi-stationary time series with power spectra Φ_u, while n_1 and n_2 are white noise sequences with spectra $\sigma^2_{n_1}$ and $\sigma^2_{n_2}$ respectively. Consequently, u, n_1 and n_2 are all mutually uncorrelated. Furthermore, we will consider prefiltered input/output data

$$y_F(t) = L(q)y(t) \qquad u_F(t) = L(q)u(t) \tag{7}$$

The objective of the parameter estimation procedure is to approximate (2) to a model according to (5). This is accomplished by minimizing the prefiltered prediction error ($e_F(t) = L(q)e(t)$)

$$\min_{\tilde{p},\tilde{p}_e} \sum_{i=1}^{N} e_F^2(i) \tag{8}$$

Using Parseval's theorem, it becomes possible to express the least-squares parameter estimation problem in the frequency domain

$$\lim_{N\to\infty} \sum_{i=1}^{N} e_F^2(i) = \frac{1}{2\pi}\int_{-\pi}^{\pi} \Phi_{e_F}(\omega)d\omega \tag{9}$$

where Φ_{e_F} is defined as

$$\Phi_{e_F}(\omega) = \frac{|L(e^{j\omega})|^2}{|\tilde{p}_e(e^{j\omega})|^2}\big(|p(e^{j\omega}) - \tilde{p}(e^{j\omega})|^2\Phi_u(\omega) + \underbrace{|p(e^{j\omega})|^2\sigma^2_{n_1} + \sigma^2_{n_2}}_{\Phi_\nu(\omega)}\big) \tag{10}$$

Equation (10) provides a number of insights regarding the significant effects in open-loop least-squares identification. The input signal power spectral density Φ_u, the choice of prefilter $L(q)$, the structure of $\tilde{p}$ and $\tilde{p}_e$, and the disturbance spectrum $\Phi_\nu(\omega)$ (further broken down into the noise variances $\sigma^2_{n_1}$ and $\sigma^2_{n_2}$) all play an important role in the resulting parameter estimates. From (10) we can infer that if $u(t)$ is a persistently exciting input (i.e., $\Phi_u \neq 0$ for all frequency) and $\tilde{p}$ and has the correct model structure, then an optimum is reached when $\tilde{p} = p$; consistent estimation of the plant model p is possible, even if the structure of the noise model $\tilde{p}_e$ is incorrect.

When addressing closed-loop direct prediction-error estimation, similar expressions to open-loop prediction-error estimation can be obtained which relate the objective function to the estimated model, the prefilter, the manipulated and disturbance transfer functions, and the closed-loop transfer functions. The closed-loop structure considered is according to Figure 1, which consists of a classical feedback structure with possible signal injection points at r and u_d.

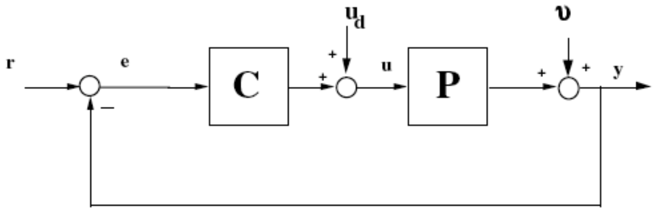

Fig. 1. Closed-loop feedback system considered in *ITCLI*, with signal injection points r and u_d, and external disturbance $\nu(t) = P(q)n_1(t) + n_2(t)$.

The derivation of the bias expression is not presented for reasons of brevity; the final result is shown below:

$$\lim_{N\to\infty} \sum_{i=1}^{N} e_F^2(i) = \frac{1}{2\pi}\int_{-\pi}^{\pi} \Phi_{e_F}(\omega)d\omega \tag{11}$$

where

$$\Phi_{e_F} = \frac{|L|^2}{|\tilde{p}_e|^2}\big(|p-\tilde{p}|^2\left(|p^{-1}\eta|^2\Phi_r + |\epsilon|^2\Phi_{u_d}\right) + |1+\tilde{p}c|^2|\epsilon|^2\overbrace{\left(|p(e^{j\omega})|^2\sigma^2_{n_1} + \sigma^2_{n_2}\right)}^{\Phi_\nu(\omega)}\big) \tag{12}$$

and

$\eta = pc(1+pc)^{-1}$ Complementary sensitivity function

$\epsilon = (1+pc)^{-1}$ Sensitivity function

The important fact to consider from (12) is that in closed-loop identification, consistent estimation of p with $\tilde{p}$ is *not* obtained even if the external signals are white noise and uncorrelated to each other. In this case, the crosscorrelation between the input signal u and the disturbance signals n_1 and n_2 is nonzero because of the action of the controller. Plainly speaking, the controller "gets in the way" of the identification, affecting the quality of the parameter estimates. Hence, in addition to the effects discussed in the open-loop case, the feedback controller c also introduces an additional source of bias to the parameter estimation problem, which must be analyzed carefully if one is to obtain adequate models from closed-loop data.

The effect of the feedback controller c is reflected in two ways. We see it in its effect on the closed-loop transfer functions ϵ and $p^{-1}\eta$, which directly weight the additive error term $p - \tilde{p}$; we also see it in the term $(1+\tilde{p}c)$, which establishes a trade-off between the magnitudes of the input signal power spectral density $\Phi_u(\omega)$ and the disturbance spectrum $\Phi_\nu(\omega) = |p(e^{j\omega})|^2\sigma^2_{n_1} + \sigma^2_{n_2}$.

We discuss first the effect of the closed-loop transfer functions ϵ and $p^{-1}\eta$. These transfer functions act as weights on the parameter estimation problem. The specific nature of these transfer functions determines what frequency ranges are attenuated or amplified. Consider the case of injecting the external signal at the manipulated variable (u_d). In this case, the closed-loop transfer function weighting the effect of u_d is the sensitivity function ϵ. For controllers with integral action, the amplitude ratio of the sensitivity function is 0 at $\omega = 0$, and increases with increasing frequency. The effect of the control system is to attenuate the low-frequency portion of the external signal, which implies that significant detuning of c may be required in order to obtain an appropriate steady-state fit. In contrast, the effect of an external signal introduced at the set point is that the signal is weighted by $|p^{-1}\eta|^2$, which does not attenuate the low frequencies when the controller is tightly tuned. However, a tightly tuned controller may also lead to amplification of the higher frequencies. Hence an "intermediate" tuning setting that does not highly amplify the high frequencies may be sensible to apply in this case.

We need to examine the effect of c as reflected in the term $(1+\tilde{p}c)$. One way of understanding this function is to view it as the reciprocal of the sensitivity function based on the *estimated* plant model. The implication of this term is that bias in closed-loop identification will be present even if u_d and d are independent, white noise sequences and $A(q) = 1$. The extent of bias on the estimate of $\tilde{p}$ will depend greatly on the magnitudes of the input signals and disturbance power spectrums. Assume for purposes of illustration that $\Phi_r = 0$ for all frequencies. Under these circumstances, the excitation in the system is driven by the external disturbance signal $\nu(t) = P(q)n_1(t) + n_2(t)$. For frequencies where $\Phi_{u_d}/\Phi_\nu \ll 1$, then $\Phi_{e_F} \approx 0$ when

$$\tilde{p} = -\frac{1}{c} \qquad (13)$$

which means that the estimated plant model approximates the inverse of the controller. For frequencies where $\Phi_{u_d}/\Phi_\nu \gg 1$ then $\tilde{p} = p$ which emphasizes the importance in closed-loop identification, of having a high input signal-to-noise ratio over the frequency range of interest.

In summary, analyzing the bias distribution in closed-loop identification indicates that for best results, substantial power in the input signals (i.e., large enough so that u_d or r have a predominant effect on y) and, if u_d is the signal injection point, substantial detuning of the controller c. While these recommendations result in greater deviations of the controlled variable from setpoint, they are fundamentally necessary in order to perform meaningful identification in the presence of feedback. Introducing the external signal at the controlled variable setpoint can reduce the need for detuning; however, a high ratio of the input signal-to-disturbance power is still necessary for low bias in the estimation.

3.2 Problems caused by variance

Similarly, there exist expressions for variance in the closed-loop that contrast those in the open-loop (Gevers et al., 2001). We shall focus primarily on the variance associated with $\tilde{p}$. In open-loop identification when u and ν are uncorrelated, the asymptotic covariance expression for unbiased estimation is

$$\text{Cov}\tilde{p}(e^{j\omega}) \sim \frac{n}{N}\frac{\Phi_\nu(\omega)}{\Phi_u(\omega)} \qquad (14)$$

where n is the model order and N is the number of data. For closed-loop identification under the feedback structure described in Fig. 1, the corresponding asymptotic covariance expression is

$$\text{Cov}\tilde{p}(e^{j\omega}) \sim \frac{n}{N}\frac{\Phi_\nu(\omega)}{\Phi_u^{\text{ext}}(\omega)} = \frac{n}{N}\left(\frac{\Phi_\nu(\omega)}{|p^{-1}\eta|^2\Phi_r + |\epsilon|^2\Phi_{u_d}}\right) \qquad (15)$$

We see the continuing effects of controller tuning, as reflected in the closed-loop transfer functions ϵ and $p^{-1}\eta$, in influencing the variance of the plant estimate, as well as the important role of the power spectral densities in the external signals r and u_d.

4. INTERACTIVE TOOL DESCRIPTION

This section summarizes the mean features of the interactive tool, which can be downloaded for free at `http://aer.ual.es/ITCLI/`. The graphical distribution of the tool has been developed according to the most important steps in a closed-loop identification problem. It is described as follows (see Fig. 2):

- *Input signal definition.* The input signal information in the tool is characterized by four different areas. A section called Input signal parameters is located at the top center zone of the tool. This section is devoted to 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. (2012b). 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 center right area and top right corner, there are two graphics namely Input signal and Power Spectrum. The graph in the top, Input signal, shows one cycle of the input signal, the graph below represents the input signal power spectrum. The input signal can be also modified dragging on both graphics. Once an input signal has been configured, the full input signal with the total number of cycles is shown in Full input signal graph, located at the left-bottom of the central part of the main screen.
- *Model estimation.* The different model structures can be selected from a set of checkboxes located on the top of the Step responses graphic, at the top left part of the tool. When a model structure is selected, estimation and validation results for that model are calculated and shown in the corresponding graphics of the tool. The model parameters can be modified from the section called Model parameters, which is available below the Input signal parameters section. Several radio buttons are available to choose between the different model structures. Once a model structure is selected, different sliders appear being possible to modify the associated orders interactively. Regarding the estimation process, once an input signal has been configured, the full input signal is applied to a high-order process model in order to obtain the simulated "real data" (shown in black in the Output signal graphic), which is used as real process data in the estimation process. In this tool, the input signal can be applied for open-loop or closed-loop identification purposes. On the top of the Full input signal graph, there are two sets of radio buttons allowing to switch between these two options. The first radio button group, located on the top right part of the Full input signal graph, allows to choose between open-loop or closed-loop identification. When the open-loop option

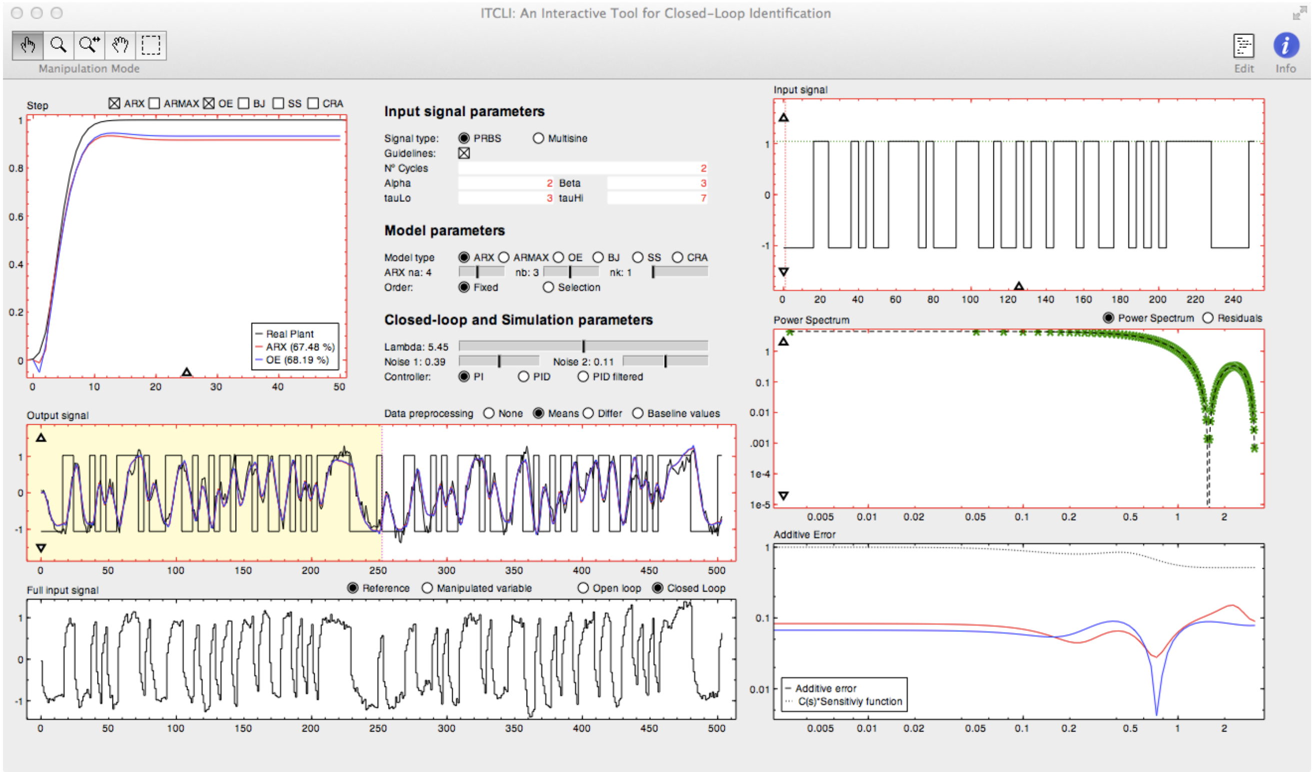

Fig. 2. Main screen of *ITCLI*, displaying results for the first illustrative example explained in Section 5, using a PRBS input introduced at the set point.

is selected, the full input signal is applied directly in open loop to the high-order model like done in *ITSIE* (Guzmán et al., 2012b). This option has been kept here to compare the results between open-loop and closed-loop identification methodologies. On the other hand, when the closed-loop option is active, the full input signal is applied in close loop on the high-order model. The input signal can be introduced in the loop at the reference or at the manipulated variable paths, and this option can be determined from the second radio button group located at the top center part of the Full input signal graph. Based on the selected option (reference or manipulated variable), the full input signal should be shown at the Output signal or Full input signal graphic, respectively. The different parameters for the closed-loop simulation are available at the Closed loop and simulation parameters section.

In the Output signal graphic, there is a interactive pink vertical line defining the estimation and validation data. The area shown in yellow (at the left of the vertical line) defines the estimation data, whereas the white area represents the validation data (at the right side of the vertical line). Therefore, when a model structure is selected, the open-loop or closed-loop estimation data is used to estimate the model parameters and the validation data to test the resulting model. Then, for each selected model structure, the full input signal is applied to the obtained model, and the results are shown in the Output signal graphic together with the original data of the high-order system. Different colors are used to distinguish between the results of each model.

- *Model validation.* As commented above, the validation data is represented in white in the Output signal graphic. This validation data is used for crossvalidation purposes. Model validation results are displayed in other two different graphics: Step Responses and Correlation function of residuals (which can be shown using the radio buttons located on the top of the Power Spectrum graphic). The Step Responses graph, which is located at the top left-hand side of the tool, shows the step responses for the each selected models and a legend representing its goodness of fit in %
- *Closed-loop identification.* The closed-loop parameters are located below the Model parameters section. PI, PID or PID with filter controller structures can be selected from three radio buttons. Moreover, a slider called Lambda allows to specify the parameter λ for the IMC filter time constant according to IMC-PID tuning rules (Rivera et al., 1986) summarized in Table 1. 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. When the closed-loop option is selected from the radio button located at top right part of the Full input signal graph, the closed-loop simulation data is shown at the Output signal or Full input signal graphics for the output and control signals, respectively. At the lower right corner of the tool, there is a graph that shows the Bode magnitude of the additive error ($|p - \tilde{p}|$) for each selected model as well as the magnitude of the sensitivity function, $|\epsilon|$, when the external signal is introduced at the manipulated variable or, $|\tilde{p}^{-1}\eta| = |c\ \epsilon|$, when the external signal is introduced at the reference. The plots of these frequency responses are very useful for

studying bias shifts and variance effects as a result of changes in controller tuning (according to the analysis in Section 3 and Equation (12)).

5. ILLUSTRATIVE EXAMPLES

We consider the simulated fifth-order system presented previously and described by the transfer function

$$p(s) = \frac{1}{(s+1)^5} \tag{16}$$

with a default sample time of $T_s = 1$ min. This plant is identified in the closed-loop using built-in PI / PID / PID w/ filter controllers obtained from *i-pIDtune*. In all these controllers, the IMC filter λ can be adjusted as part of the tool. The magnitude-only Bode plots for the closed-loop transfer functions are evaluated (along with the additive error) and shown in the bottom right of the *ITCLI* screen.

Three cases are shown in this paper as part of this example. In the first two cases, a PRBS input signal is used for identification, with parameters: $m = 2$ (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), $\tau_{\text{dom}}^L = 3$ (low estimate of τ_{dom}) and $\tau_{\text{dom}}^H = 7$ (high estimate of τ_{dom}). For more information about these parameters see Guzmán et al. (2012b).

The two different signal injection points r and u_d are evaluated. Results are shown in Figure 2 for the case of external excitation at the reference set point; both ARX and OE model structures are estimated. Working with the tool shows that controller tuning during this identification must be at some "intermediate" level; that is, the amplitude $|p^{-1}\eta|$ must be as flat as possible. The second result, shown in Figure 3, shows that for the same external input, but now introducing the signal at the manipulated variable, the controller must be detuned substantially through a significant increase in λ. Despite the detuning, the low frequencies are still being attenuated by the action of the controller, and consequently the steady-state gain is not estimated as precisely compared to the set point case.

The final result, shown in Figure 4, illustrates one of the main points stressed in Section 3 regarding the reasons why external excitation in closed-loop identification is so important. In this case, the excitation in the data is provided completely by the disturbance signal $\nu(t)$; the external input magnitude is lowered effectively to zero. Here we see how closed-loop identification displays a perfect fit to data from completely erroneous models. This is illustrated for both ARX and Output Error identification.

6. CONCLUSIONS

This paper describes an interactive tool for evaluating important aspects of closed-loop identification. By using *ITCLI* it is possible to achieve this understanding interactively; this being the motivating philosophy behind the methodology described in this paper. The tool provides different functionality modes which make it possible for students and engineers to use its capabilities with a small learning curve. The tool is available free of charge from `http://aer.ual.es/ITCLI/`. Future work will be oriented to include prefiltering as a design variable in closed-loop identification, and include other illustrative model examples beyond the fifth-order system. A comparisons to alternative forms of identification under closed-loop settings (such as relay feedback, Liu et al. (2013)) are being contemplated.

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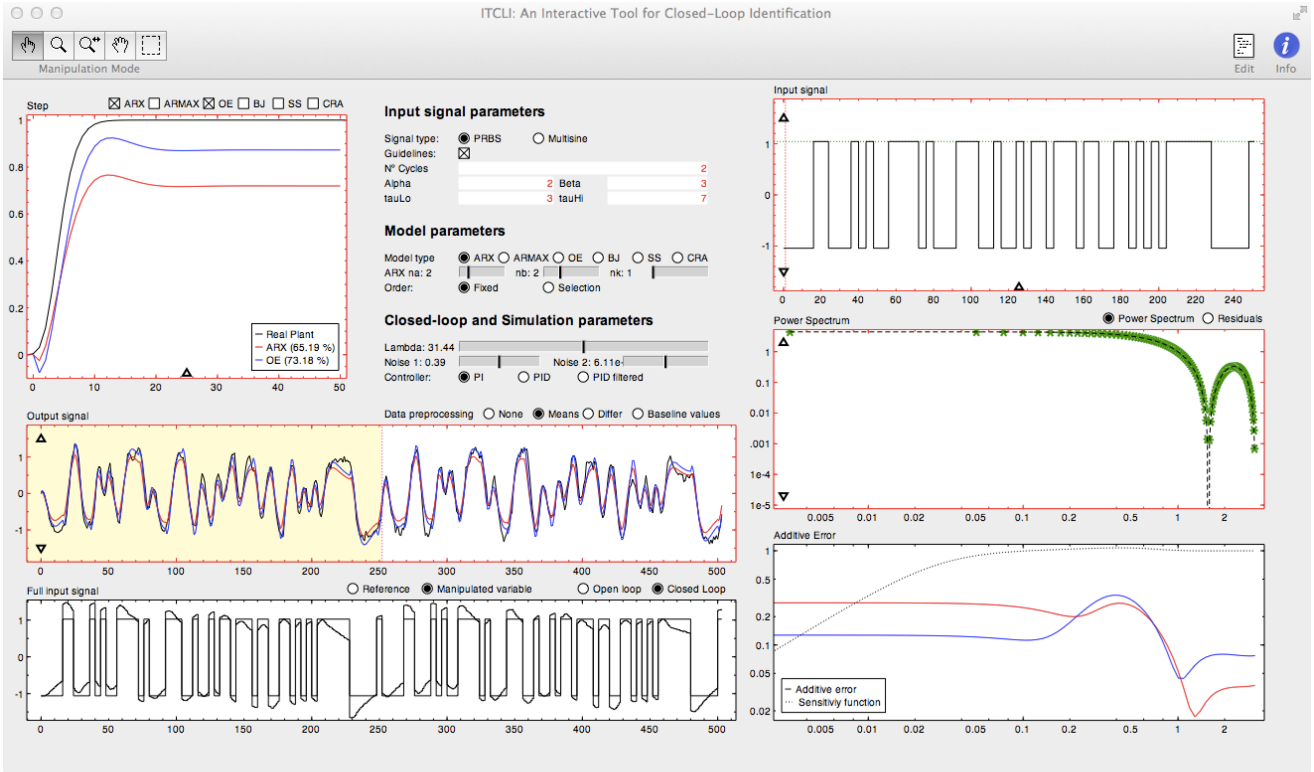

Fig. 3. Results for the second illustrative example explained in Section 5. Here the external excitation is introduced at the manipulated variable, with the closed-loop system needing to be detuned substantially to achieve identification with low estimation error. Despite this, precise estimation of the steady-state gain is difficult to achieve.

Fig. 4. Results for the third illustrative example explained in Section 5. If only excitation from disturbances is considered, it is possible in closed-loop identification to fit to data "perfectly" with highly erroneous models. This motivates the need for a sensibly designed external input signal.