ITCRI: An Interactive Software Tool for Control-Relevant Identification Education

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Abstract: This paper describes the theoretical basis, features, and functionality of an interactive software tool focused on control-relevant identification education. The **I**nteractive **T**ool for **C**ontrol **R**elevant **I**dentification (*ITCRI*) comprehensively captures the control-relevant identification process, from input design to closed-loop control, depicting these stages simultaneously and interactively in one screen. Control-relevance in *ITCRI* is accomplished primarily through prefiltering, which is evaluated using single-pass and two-step algorithms. By simultaneously displaying both open- and closed-loop responses of the estimated models and important control-relevant validation criteria (such as the multiplicative error), *ITCRI* 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. This tool has been developed using Sysquake and is delivered as a stand-alone executable program that is readily accessible for students and users.

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

1. INTRODUCTION

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 be directly suitable for control system 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; Casini et al., 2004; Nassirharand, 2008). 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., 2009a,b). It includes all stages of system identification in the same screen, with the different stages connected interactively in such a manner that a modification in one stage is automatically visualized in the remaining ones. *ITSIE* focuses, however, exclusively on open-loop system identification; the current work goes beyond this to explore the problem of control-relevant identification.

The main objective of this paper is to describe the theory, features, and application of a novel **I**nteractive **T**ool for **C**ontrol **R**elevant **I**dentification (*ITCRI*) for educational purposes. The tool considers the control-relevant estimation of low-order ARX and Output Error models conforming to the IMC Prett-García PID tuning rules. To achieve this aim, two prefiltered prediction-error estimation procedures are considered. The first estimates the low-order models directly from prefiltering of the input/output data. The second follows a two-step procedure where a high-order ARX model is estimated first, followed by control-relevant model reduction (using iterative prefiltering) of the ARX model’s impulse response. The prefilters are systematically defined from closed-loop performance requirements and the setpoint/disturbance changes to be faced in the control problem. The interactive tool enables understanding how the tuning parameter of the prefilter directly influences both the open and closed-loop responses of the system. Validation criteria allow the user or student to check: (i) how control-relevant modeling keeps the error low over a bandwidth defined by the control requirements specified by the user and (ii) how open-loop error in the model translates into adequate or poor closed-loop behavior. The interactive tool is coded in Sysquake, a Matlab-like language with fast execution and excellent facilities for interactive graphics (Piguet, 2004). Executable files for the modules that do not require the Sysquake software to operate, are in public domain and available for Windows, Mac, and Linux operating systems.

The paper is organized as follows. First, a brief description of the theoretical background behind the tool is presented in Section 2, with a description of the control-relevant estimation algorithms in Section 3. In Section 4 the functionality of the tool is described; an illustrative example is presented in Section 5. Finally, Section 6 presents the main conclusions and future research work.

2. THEORETICAL BACKGROUND

This section is devoted to a description of the theoretical background behind the interactive tool. Because *ITCRI* and *ITSIE* share some common functionailty, the points which refer exclusively to control-relevant identification are emphasized.

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:

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

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 Digital PID controller design

Prett and García (1988) present an algorithm for digital PID controller design which is based on the Internal Model Control (IMC) design procedure for discrete-time models (Morari and Zafiriou, 1997). These PID controllers possess the feature that they have a single adjustable parameter $\delta = \exp(-T_s/\lambda)$ which is directly linked to the closed-loop speed of response λ. In *ITCRI*, second-order plants without integrator are identified according to the tuning rules summarized in Table 1, resulting in Prett and García (1988) controllers of the general form:

$$\Delta u_k = K_c[e_k - \tau_I e_{k-1} + \tau_D e_{k-2}] + \tau_F \Delta u_{k-1} \tag{2}$$

where $\Delta u_k = u_k - u_{k-1}$ is the change in controller output and $e_k = r - y_k$ is the setpoint tracking error. The parameters K_c, τ_I, τ_D and τ_F are coefficients of the difference equation in Eq. (2) and are not equivalent to the continuous PID controllers parameters.

Table 1. Prett-García Digital PID Controller Parameters for Low-Order Models. ($0 < \delta < 1$, $\delta = \exp(-T_s/\lambda)$ is an adjustable parameter; T_s is the sampling time.

	$\tilde{p}(q)$	$\tilde{\eta}(q)$	KK_c	τ_I	τ_D	τ_F
A^a	$\frac{K(q-\beta)}{(q^2-\alpha_1 q+\alpha_2)}$	$\frac{1-\delta}{q-\delta}$	$1-\delta$	α_1	α_2	β
B^b	$\frac{K(q-\beta)}{(q^2-\alpha_1 q+\alpha_2)}$	$\frac{1-\delta}{q-\delta}\frac{q-\beta}{1-\beta q}$	$\frac{1-\delta}{-\beta}$	α_1	α_2	$\frac{\delta(1+\beta)}{\beta}-1$
C^c	$\frac{K(q-\beta)}{(q^2-\alpha_1 q+\alpha_2)}$	$\frac{1-\delta}{q-\delta}\frac{q-\beta}{(1-\beta)q}$	$\frac{1-\delta}{1-\beta}$	α_1	α_2	$\frac{(1-\delta)\beta}{1-\beta}$

[a] $0 \le \beta < 1$ [b] $\beta \ge 1$ [c] $\beta < 0$

2.3 Model structure selection and parameter estimation

The interactive tool examines the general family of prediction-error (PEM) models which corresponds to

$$A'(q)y(t) = \frac{B'(q)}{F'(q)}u(t-nk) + \frac{C'(q)}{D'(q)}e(t) \tag{3}$$

$$y(t) = \tilde{p}(q)u(t) + \tilde{p}_e(q)e(t) \tag{4}$$

In Eq. (4) $\tilde{p}(q)$ refers to the estimated plant model and $\tilde{p}_e(q)$ is the noise model. $A'(q)$, $B'(q)$, $C'(q)$, $D'(q)$ and $F'(q)$ are polynomials in q, and the roots of $A'(q)$ and $B'(q)$ are the poles and zeros of the plant, respectively. The two PEM models used in *ITCRI* for control-relevant identification are shown in Table 2.

Table 2. Prediction-error model structures evaluated in *ITCRI*.

Method	$\tilde{p}(q)$	$\tilde{p}_e(q)$
ARX	$\frac{B'(q)}{A'(q)}q^{-nk}$	$\frac{1}{A'(q)}$
Output Error	$\frac{B'(q)}{F'(q)}q^{-nk}$	1

Control-relevant identification in *ITCRI* is accomplished via prefiltered prediction error estimation,

$$\arg \min_{\tilde{p},\tilde{p}_e} \frac{1}{N}\sum_{i=1}^{N} e_F^2(i) \tag{5}$$

where $e_F(t) = L(q)e(t)$ is the prefiltered prediction error, and $L(q)$ is the prefilter. 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 the prefilter and other identification design variables. As the number of observations $N \to \infty$, the least-squares estimation problem denoted by (5) can be written as:

$$\lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} e_F^2(i) = \frac{1}{2\pi}\int_{-\pi}^{\pi} \Phi_{e_F}(\omega)d\omega \tag{6}$$

where $\Phi_{e_F}(\omega)$, the prediction-error power spectrum is

$$\Phi_{e_F}(\omega) = \frac{|L_e(e^{j\omega})|^2}{|\tilde{p}_e(e^{j\omega})|^2}\left(|p(e^{j\omega}) - \tilde{p}(e^{j\omega})|^2\Phi_u(\omega) + |p(e^{j\omega})|^2\sigma_{n_1}^2 + \sigma_{n_2}^2\right) \tag{7}$$

Equation (7) helps explain systematic bias effects in identification, which can be readily explored in *ITCRI*. This includes issues relating to the spectral content in the input signal, bias that is introduced (or removed) by the choice of model structure (particularly the noise model), and the associated multi-objective optimization problem resulting from varying magnitudes of the noise variances $\sigma^2_{n_1}$ and $\sigma^2_{n_2}$. Most importantly, Equation (7) shows that prefiltering acts as a frequency-dependent weight on the goodness-of-fit in prediction-error estimation. How to properly design this prefilter to take into account closed-loop performance requirements is the focus of the ensuing section.

2.4 Control-Relevant Parameter Estimation

The model structures required by the controllers in Table 1 are often times too simple to describe the entire dynamic behaviour of the plant. However, control requirements can narrow the regions of time and frequency over which an adequate model fit is necessary. Therefore, the objective of the control-relevant identification process is to obtain improved models over the frequency band of importance of the control problem. To fulfill this objective a control-relevant prefilter from the 2-norm closed-loop objective function is developed, which acts as a frequency-dependent weight on the parameter estimation problem and systematically incorporates control requirements in the parameter estimation problem (Rivera et al., 1992).

Control-relevance thus requires that one define the control problem for which the model is intended. In this work, the control-relevant estimation it is exclusively focused on a plant model $\tilde{p}$ to be used for single degree-of-freedom feedback control using the tuning rules given in Prett and García (1988). The control objective is to minimize the 2-norm of the control error $e_c = (r - y)$

$$\|e_c\|_2 = \left(\sum_{k=0}^{\infty} e_c^2(k)\right)^{1/2} \tag{8}$$

The feedback controller $c(q)$ that is assumed to be a single degree-of-freedom, is designed on the basis of $\tilde{p}(q)$. Resulting in the following nominal response transfer function:

$$\tilde{\eta}(q) = \tilde{p}(q)c(q)\left(1 + \tilde{p}(q)c(q)\right)^{-1} \tag{9}$$

$$\tilde{\epsilon}(q) = (1 - \tilde{\eta}(q)) = (1 + \tilde{p}(q)c(q))^{-1} \tag{10}$$

where $\tilde{\epsilon}$ is the sensitivity operator of the closed-loop system and $\tilde{\eta}$ is the complementary sensitivity operator (Morari and Zafiriou, 1997). When $c(q)$ is implemented on the plant $p(q)$, the deterioration in control performance caused by plant/model mismatch is

$$e_c(q) = \frac{\tilde{\epsilon}(q)}{1 + \tilde{\eta}(q)e_m(q)}(r - d) \tag{11}$$

where $e_m(q) = (p(q) - \tilde{p}(q))\,\tilde{p}^{-1}(q)$ is the multiplicative error between the true plant and the calculated model. Stability of $c(q)$ on $\tilde{p}(q)$ does not ensure stability with regards to $p(q)$. A computationally simpler stability requirement used for stability is the small gain theorem:

$$|\tilde{\eta}\left(e^{j\omega}\right) e_m\left(e^{j\omega}\right)| \leq 1 \qquad \forall -\pi \leq \omega \leq \pi \tag{12}$$

When Eq. (12) holds, Eq. (11) can be approximated by a first term Taylor series if $|\tilde{\eta}\left(e^{j\omega}\right) e_m\left(e^{j\omega}\right)| \ll 1$ over the bandwidth defined by $\tilde{\epsilon}(q)(r - d)$.

$$e_c(q) \approx \tilde{\epsilon}(q)\left(1 - \tilde{\eta}(q)e_m(q)\right)(r - d) \tag{13}$$

The control objective function that appears in Eq. (8), can be approximated by substituting Eq. (13) into Eq. (8). Once expressed the approximation in the frequency domain via Parseval's Theorem, the statement of the control-relevant parameter estimation problem is obtained by minimizing the contribution arising from identification error:

$$\min_{\tilde{p}} \left(\frac{1}{2\pi}\int_{-\pi}^{\pi} |\tilde{\epsilon}\left(e^{j\omega}\right)|^2 |\tilde{\eta}\left(e^{j\omega}\right)|^2 |r - d|^2 |e_m\left(e^{j\omega}\right)|^2 d\omega\right)^{1/2} \tag{14}$$

Equation (14) is the problem whose solution is solved in the time domain by means of prefiltered ARX and Output Error (OE) estimation. As presented in Rivera et al. (1992), the relationship between Equation (7) and (14) leads to a general definition for the control-relevant prefilter:

$$L(q) = \tilde{p}_e(q)\tilde{p}^{-1}(q)\tilde{\epsilon}(q)\tilde{\eta}(q)(r(q) - d(q)) \tag{15}$$

It is important to highlight the components that form the prefilter $L(q)$:

- The closed-loop transfer functions $\tilde{\eta}(q)$ and $\tilde{\epsilon}(q)$ that define the closed-loop speed of response.
- The setpoint/disturbance direction $(r(q) - d(q))$.
- The identified plant and noise models $\tilde{p}(q)$ and $\tilde{p}_e(q)$.

Since $\tilde{p}(q)$ is initially unknown, the implementation of the prefilter is inherently iterative. However, in *ITCRI* two algorithms to calculated the prefilter are implemented: (i) a rigorous iterative implementation that is applied to an ARX high order model and (ii) a simplified non-iterative alternative that is applied directly to the data. These are summarized in the ensuing section.

3. CONTROL-RELEVANT ESTIMATION ALGORITHMS

The *ITCRI* tool evaluates two alternate procedures for arriving at a control-relevant low-order model conforming to the Prett-Garcia PID tuning rules. In both cases, prefiltering is applied. These are described below:

Direct one-step approach using input/output data.
ARX-221 or OE-221 models are obtained directly from the prefiltered input-output data.

Two-step approach from a full-order estimated model.
A high-order ARX model is obtained first, followed by control-relevant model reduction to an ARX-221 or OE-221 model structure. The control-relevant model reduction step is accomplished via iterative prefiltered estimation.

The reader is referred to Rivera et al. (1992) where the iterative and direct (single-pass) algorithms are presented with some examples; moreover, a more detailed description of the iterative case appears in Rivera and Gaikwad (1996). A summary of the procedures is enclosed below:

3.1 Single-pass prefilter applied to data

This algorithm requires that the user specify up-front reasonable estimates for the dominant plant time constant and desired closed-loop speed of response, and substitute these into (15). For $\tilde{\eta}$, the following structure is used

$$\tilde{\eta}(q) = q^{-nk} f(q) \tag{16}$$

where the order of $f(q)$ is dictated by the control design procedure. In *ITCRI*, the second-order filter structure

$$f(q) = \frac{(1-\delta)^2 q^2}{(q-\delta)^2} \tag{17}$$

is used, where $\delta = \exp(-1.555 T_s/\tau_{cl})$, with τ_{cl} being the anticipated closed-loop time constant. Furthermore, *a priori* knowledge of the plant dominant time constant is used to approximate $\tilde{p}$ as:

$$\tilde{p}(q) = \frac{q^{-nk+1}}{(q-\alpha)} \tag{18}$$

where $\alpha = e^{-Ts/\tau_{dom}}$ and τ_{dom} is an estimate of the dominant time constant of the system. For OE estimation, $\tilde{p}_e = 1$, while for ARX models, $\tilde{p}_e$ can be approximated with the same dominant time constant guess made for $\tilde{p}$:

$$\tilde{p}_e(q) = \frac{q}{(q-\alpha)} \tag{19}$$

3.2 Two-step, iterative prefiltering approach

In the two-step approach, the first step consists of estimating a full-order PEM model that meets classical validation criteria (e.g., white residuals uncorrelated with the input). In *ITCRI*, this full-order model is estimated via high-order ARX estimation, which can be consistently estimated if a persistently exciting input is used (Ljung, 1999). The second step consists of a model reduction, in which the impulse response of the full-order model is reduced to a restricted complexity form as summarized in Table 1. The impulse response of the full-order plant can be adequately represented by a FIR model:

$$\begin{aligned} y(t) &= B(q)\; u(t-1), \\ B(q) &= b_1 + b_2 q^{-1} + \ldots + b_{n_b} q^{-n_b+1} \end{aligned} \tag{20}$$

The goal is to approximate Eq. (20) with a low-order ARX model according to:

$$A'(q)y(t) = B'(q)u(t-1) + e_r(t) \tag{21}$$

where

$$\begin{aligned} A'(q) &= 1 + a'_1 q^{-1} + \ldots + a'_{n'_a} q^{-n'_a} \\ B'(q) &= b'_1 + b'_2 q^{-1} + \ldots + b'_{n'_b} q^{-n'_b+1} \end{aligned}$$

and n'_a and n'_b are low-numbered integers (1 or 2); in *ITCRI*, $n'_a = 2$ and $n'_b = 2$. In this method the prediction error $e_r(t)$ represents the model reduction error. The objective minimized in ARX identification is the squared filtered prediction error ($e_f(t) = L(q)e_r(t)$) which for $N \to \infty$ can be written equivalently in the frequency domain as

$$V = \frac{1}{2\pi} \int_{-\pi}^{\pi} \left| B(e^{j\omega}) - \frac{B'(e^{j\omega})}{A'(e^{j\omega})} \right|^2 |A'(e^{j\omega})|^2 |L(e^{j\omega})|^2 \Phi_u(\omega) d\omega \tag{22}$$

where $\Phi_u(\omega)$ represents the power spectra for the input. Because the model reduction step is applied to a noise-free data set (i.e., the full-order model's impulse response), the influence of noise n_1 and n_2 is greatly reduced, in contrast to more general PEM estimation as seen in (7). The definition of the prefilter is obtained by comparing the frequency-domain expressions of the prefiltered ARX problem that appear in Eq. (22) to that of the control-relevant parameter estimation problem in Eq. (14). Since $u(t)$ is an impulse, ($\Phi_u(\omega) = 1 \;\forall\; \omega$) this leads to:

$$L(q) = B'(q)^{-1} \tilde{\epsilon}(q) \tilde{\eta}(q)(r(q) - d(q)) \tag{23}$$

Thus, the iterative method to calculate the prefilter for open-loop stable systems is composed of five steps.

(1) *Performance specification.* From Table 1, the user chooses the structure for $\tilde{p}$ and $\tilde{\eta}$. The engineer must only specify the value for the closed-loop time constant λ, which in turn defines the value of the filter adjustable parameter according to $\delta = \exp(-T_s/\lambda)$.

(2) *Initialization.* Here $y(t)$, the finite impulse response, and $u(t)$ (a unit pulse input) are filtered using $L(q)$ defined according to Eq. (23) with

$$B'(q) = 1 \qquad \tilde{\eta}(q) = \frac{(1-\delta)}{q-\delta} \qquad r - d = \frac{q}{q-1}$$

One must now perform ARX estimation using $y_F(t)$ and $u_F(t)$ (the prefiltered output and input) to obtain an initial estimate for the reduced-order model $\tilde{p}$.

(3) *Iteration.* Use the models $\tilde{p}(q)$ and $\tilde{p}_e(q)$ obtained from initialization or from the previous iteration to update $B'(q)$, $\tilde{\eta}(q)$ and thus, define a new $L(q)$. Proceed then to prefilter $y(t)$ and $u(t)$ and redo ARX estimation.

(4) *Termination.* This step determines if iteration needs to be completed. For this aim, two criteria are used. If the objective function does not change by a specified amount:

$$|V_{current} - V_{previous}| \leq TOL \tag{24}$$

and the parameters of $\tilde{p}$ change by less than a user-defined tolerance, then terminate. Otherwise, complete another iteration.

(5) *Validation.* Once iterations have converged, one must verify that: (i) the estimated model is stable and, (ii) the small gain condition in Eq. (12) has been satisfied. Failure to satisfy these criteria imply that either the closed-loop speed of response must decrease, or the order of the model must increase.

3.3 Model validation

ITCRI provides classical methods for validation which include simulation, crossvalidation, residual analysis on the prediction errors (for full-order ARX modeling), and step responses. The percent output variance explained by each model on the crossvalidation data set is also reported. For control-relevant validation, a valuable metric is to compare the multiplicative error e_m with the prefilter $L(q)$; a good control-relevant model will display low $|e_m|$ over the bandwidth denoted by $L(q)$. Ultimately, the most informative piece of control-relevant model validation is the closed-loop response resulting from the estimated model, which in the *ITCRI* tool is contrasted simultaneously with the open-loop response.

3.4 Experimental design and data preprocessing

The input signals used in *ITCRI* are: (i) Pseudo-Random Binary Sequences (PRBS) and (ii) multisine signals. In the tool the input signal can be designed by means of direct parameter specification or applying time constant-based guidelines. The input signal guidelines and parameters are shared with the previous work presented in Guzmán et al. (2009a). Thus, for the sake of brevity the interested reader is referred to Guzmán et al. (2009a,b) for a detailed description of this component of the tool.

ITCRI data preprocessing supports mean subtraction, differencing, and substraction of baseline values, whereas mean detrending is applied by default.

4. 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/ITCRI/` (see Fig. 1) and personally experience its interactive features since it does not require a Sysquake license in order to execute.

The plant to be identified can be loaded indicating the transfer function for both the model and the prefilter. This can be done form the menu option *Mode → Simulation*. 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., 2009a,b). 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 bottom left corner, there are two graphics namely Input signal and Power Spectrum or AutoCorrelation depending on the chosen option. The graph above, 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 bottom of the central part of the main screen. When the checkbox Filtered Data is activated, the input signal is filtered too.
- *Process definition.* Below the section Input signal parameters, there is another section called Model parameters, where there are two radio buttons that allow to choose between ARX and OE, i.e. the type of model used for control-relevant identification. The order of the model, see Table 2.3, is limited to $n_a = 2$, $n_b = 2$ and $n_k = 1$ for ARX model, and $n_f = 2$, $n_b = 2$ and $n_k = 1$ for OE model. By default, the tool calculates a high-order ARX model, ARX OS, to compare with the low-order models calculated through control-relevant identification. Note that, the n_a, n_b and n_k values of this high-order model appear also in the section Model parameters. Depending on the type of model used for control-relevant identification, one or two sliders will appear to determine the values of the two parameters needed for single pass prefiltered estimation (Pref): the dominant plant-time constant (O-L Tau), only for the OE model, and the desired closed-loop speed of response (C-L Tau) for both the ARX and the OE models. Once a plant structure is selected, the full input signal applied to the simulated plant with noise is showed in black in the graph called Output signal located at the center of the main screen. This input signal is used to obtain the simulated "real data", which are then used as real process data in the estimation and validation process. In this graph, an interactive magenta vertical dashed line defines the estimation (yellow area) and validation data (white area) sets.
- *Closed-loop specification.* In the section Closed loop and simulation parameters, at the center of the left side of the main screen, the parameter λ for the IMC filter time constant (first-order filter only) which is used by the Prett-Garcia controller (Prett and García, 1988), 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.
- *Model validation.* The magenta-colored vertical line of the Output signal graphic is interactively used to define the estimation and validation data 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. Note that, this last one only appears if the checkbox Residuals is activated. The Step Responses graph, which is located at the upper right-hand side of the tool, shows the step responses for the following models: (i) ARX-OS: an ARX high-order model, green solid line, (ii) Non-Pref: depending on the chosen type of model, an ARX or OE low-order model without prefiltering, red or blue solid line respectively, (iii) Pref: depending on the chosen type of model, an ARX or OE low-order model prefiltered with the single-pass prefilter implementation, red or blue dashed line respectively, and,(iv) Iter: an ARX low-order model prefiltered with the iterative prefilter implementation, magenta solid line. Together with the step response of the models, a legend representing its goodness of fit in % is showed. Confidence intervals can be also shown in this graphic activating this option from the Parameters menu. In the Correlation function of residuals graphic, at the left of the Step responses graphic, the same color distribution explained previously is used to represent the results of each model. Moreover, above of this graphic there are two radio buttons that allow to commutate between this graphic and others two called Open-Loop Frequency Response and Multiplicative Error. In the first one,

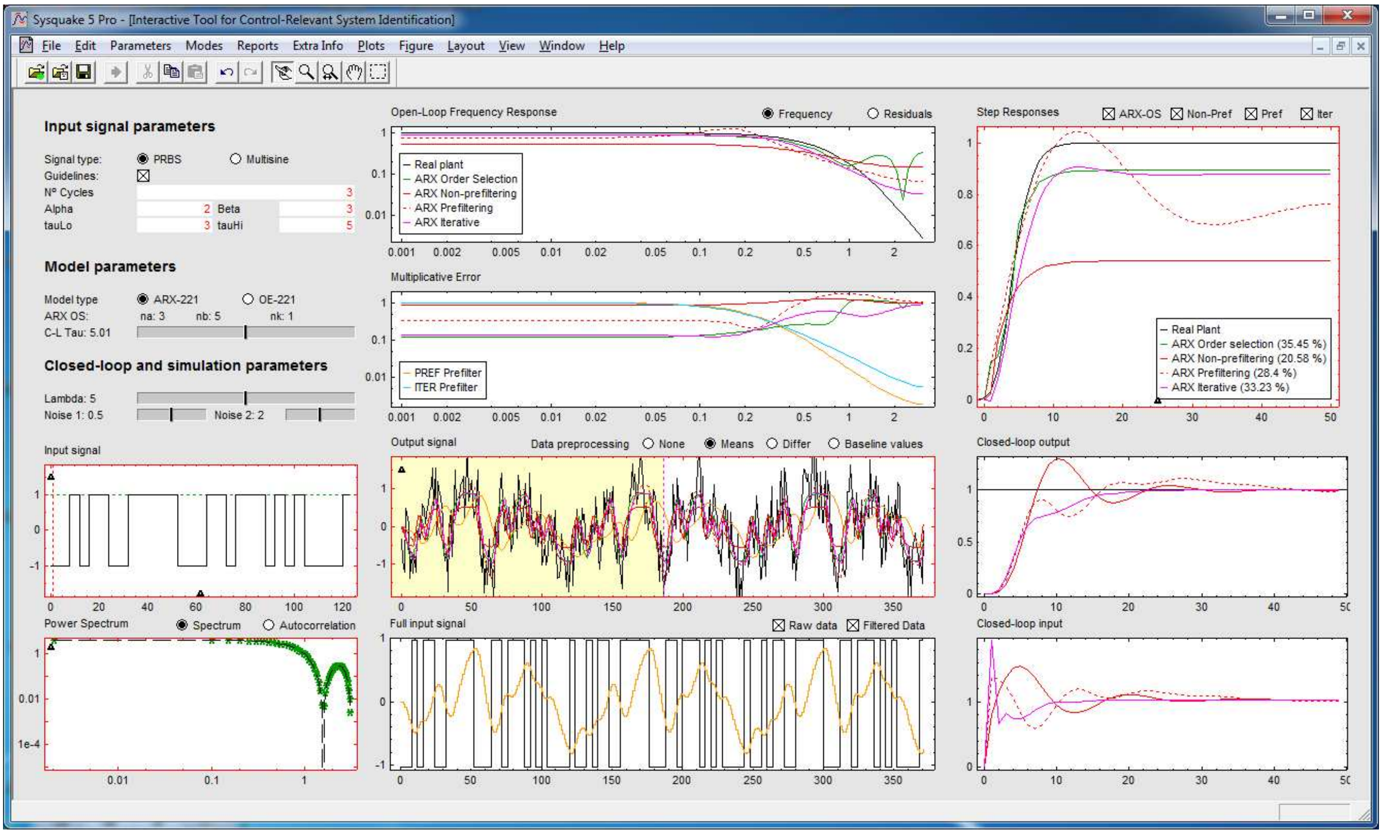

Fig. 1. Main screen of Interactive Software Tool for Control-Relevant Identification *ITCRI*, displaying results for the illustrative example explained in Section 5.

the frequency response of the calculated models is showed. In the second one, the frequency response of the multiplicative error produced by each model is showed together with the frequency response of both the iterative and the single-pass prefilters.

- *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.

5. ILLUSTRATIVE EXAMPLE

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

$$p(s) = \frac{1}{(s+1)^5} \tag{25}$$

with a default sample time of $T_s = 1$ min. The main aim of this example is to compare both prefilters, the one calculated with the iterative algorithm and the other one calculated with the single-pass algorithm. Results of this comparison are shown in Fig. 1. A PRBS input signal is used for identification, with parameters: $m = 3$ (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 the dominant time constant) and $\tau^H_{\text{dom}} = 5$ (high estimate of the dominant time constant). For more information about these parameters (see Guzmán et al. (2009a,b)). Moreover, the noise on the output signal, $n_2(t)$ in Eq. (1), is augmented to a value of 2, whereas the noise on the disturbance ($n_1(t)$ in Eq. (1)), is set to 0.5.

A high-order ARX model, with a structure of ARX-[3 5 1], is obtained from this identification signal. Its open loop response is shown in the Step Responses graph (ARX-OS), at the upper right-hand side of the tool, together with the response of three ARX low-order models (ARX-[2 2 1]): (i) Non-Pref, an ARX model without prefiltering, (ii) Pref, an ARX low-order model prefiltered with the single-pass prefilter implementation, and (iii) Iter, an ARX low-order model prefiltered with the iterative prefilter implementation. The validation criteria indicates the poor fit of these models. This is due to the high value of the noise signals n_1 and n_2, since ARX model estimation involves a tradeoff between the fit to the noise model and the fit to the transfer function. Notice that the ARX-OS model displays the highest goodness of fit in %. Regarding to closed-loop parameters, the filter parameter λ of the IMC controllers is set to a value of $\lambda = 5$. The closed-loop time constant estimation used in the prefilter, Pref model, is also set to $\tau_{cl} = 5$.

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 without prefilter (red solid line in the graphs), with a large overshoot of 30 % of the setpoint change magnitude. This fact is due to the high level of the noise in the data, which does not allow a good fit of the open loop model Non-Pref. From the Step Responses graph, it is possible to note how there is a substantial mismatch in the static gain between the Non-Pref model and the real plant.

In the case of the Pref model, the prefilter is calculated with the single-pass algorithm, PREF Prefilter and applied directly to the noisy input/output data in order to calculate an ARX model, Pref. The frequency response of both the prefilter and the multiplicative error associated with the ARX model can be observed in the Multiplicative Error graph, where it is possible to note how the prefilter enables the ARX model to achieve the control requirements imposed by specifiying $\tau_{cl} = 5$. Although the Pref model displays a poor fit with an open-loop response that resembles an underdamped system, as seen in Fig. 1 the closed-loop response from this model is much better than the previous model, Non-Pref, with a substantial reduction in overshoot as a result of control-relevant modeling.

The third model, Iter, is calculated from the high-order ARX model (ARX-OS) through the iterative prefiltering method, Iter Prefilter. Its frequency response, together with the multiplicative error associated with the Iter model, are shown in the Multiplicative Error graph. With the two step approach, it is possible to calculate an ARX model that better fulfills control requirements in comparison to the Pref model. The multiplicative error for the Iter model (Magenta line) is the lowest of all control-relevant reduced-order models, matching closely the error of the high-order ARX model (green line) up to a few multiples past the bandwidth of the iterative prefilter (Iter Prefilter, orange solid line). The closed-loop controlled variable response (magenta solid line) displays no overshoot, very little oscillation, and the fastest settling time of all three reduced-order controllers evaluated.

6. CONCLUSIONS

In this paper, an interactive tool to perform the main stages of the control-relevant identification process has been developed. 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/ITCRI/`.

The interactive tool allows the student to compare the closed-loop results from different models which have been developed with and without prefiltering. Moreover, the student can discover that some models resulting from identification are not suitable for control, since they have not been designed taking into account control requirements. The example included in this work illustrates these features, by comparing three ARX models, two of them estimated from control-relevant prefiltering and the remaining one without prefilter. Although the three models fit the open-loop data poorly due to the high magnitude of noise in the data, the two models calculated from control-relevant prefiltering display better closed-loop performance since the prefilter allows the models to emphasize a goodness-of-fit in the regions of time and frequency most important for meeting control requirements. Between these two models, the one calculated from an ARX high-order model through the two-step iterative algorithm obtains better results that the one calculated from the single pass method; these benefits are achieved, however, at the expense of identifiying a high-order ARX model first as a precursor model, and the additional computations involved in the iterative algorithm.

Future efforts include an extension to multivariable problems, the ability to import real data, and an evaluation of closed-loop control-relevant identification.

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