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ITSIE: An Interactive Software Tool for System Identification Education

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Abstract: The paper describes the conceptual basis and functionality of *ITSIE*, an Interactive Tool for System Identification Education. The tool is developed using Sysquake, a Matlab-like language with fast execution and excellent facilities for interactive graphics, and is delivered as a stand-alone executable that is readily accessible to students and users. The tool focuses on the open-loop identification of a SISO fifth-order system subject to multiple noise sources using classical prediction-error methods. The various stages of system identification, ranging from input signal design using PRBS and multisine signals through model validation are evaluated simultaneously and interactively in one screen. The highly visual and strongly coupled nature of system identification is very amenable to interactive tools, and the tool presented in this paper enables students to discover a myriad of important identification topics with a much lower learning curve than existing methods. Plans for additional tools in the series are discussed.

Keywords: System identification education, interactivity, experimental design, prediction-error estimation, model validation.

1. INTRODUCTION

Advances in information technologies have resulted in novel instructional methods that increase student motivation and improve educational outcomes. In the control engineering field, *interactive tools* have resulted in particularly useful techniques with high impact on control education [Dormido et al., 2005, Guzmán et al., 2005, Guzmán, 2006, Guzmán et al., 2008b]. 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. As a consequence of interactivity, the impact of problem variables chosen in one step can be contrasted “on the fly” with specifications made in other problem stages; such functionality has clear benefits for both educator and student [Dormido, 2004].

System identification is a field rich in visual content that can be represented intuitively and geometrically [Ljung, 2003]. Furthermore, system identification methodologies in general involve a series of sequential yet integrated stages (experimental design, model structure selection, parameter estimation, and validation) where the outcome of one stage will have a profound effect on the others. Consequently, the ability to implement identification techniques interactively is expected to have an impact on both system identification education and practice. The objective of this paper is to present the initial offering in a series of interactive learning tools that are being developed by the authors for the purpose of exploring this vast untapped potential of interactivity in the identification field. The tool draws from the experience of the authors in teaching system identification courses in both short and semester-long formats, and to diverse audiences.

The interactive tool is coded in Sysquake, a Matlab-like language with fast execution and excellent facilities for interactive graphics [Piguet, 2004], and is delivered as a stand-alone executable that makes it readily accessible to users [Guzmán et al., 2008a]. The tool consists of graphical interfaces depicting the various stages of system identification. The paper focuses on describing an introductory tool that examines the integrated effect of experimental design and model structure selection on prediction-error estimation of a SISO linear high-order system under noise. Both pseudo-random binary sequence (PRBS) and minimum crest factor multisine inputs are applied for ARX, ARMAX, Output Error (OE), Box-Jenkins (BJ), and State Space (SS) estimation of this system [Braun et al., 2002]. Experimental duration, specifying estimation and crossvalidation data sets, input signal bandwidth and magnitude, and model structure are evaluated under varying signal-to-noise ratios, with all results computed and displayed interactively to the user.

The paper is organized as follows: the theoretical background behind *ITSIE* is described in Section 2. A summary of the tool’s functionality is presented in Section 3, with a series of illustrative examples described in Section 4. The paper concludes with a brief discussion of development plans for the future.

2. THEORETICAL BACKGROUND

In *ITSIE*, the plant to be identified consists of a fifth-order system according to

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

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

$$y(t) = p^*(q)\ (u(t) + n_1(t)) + n_2(t). \qquad (2)$$

In (2), $y(t)$ is the measured output signal and $u(t)$ is the input signal that is designed by the user. $p^*(q)$ is the zero-order-hold-equivalent transfer function for $p(s)$, where q is the forward-shift operator. The system is subject to two stationary white noise sources (n_1 and n_2) introduced at different locations in the plant. n_1 allows evaluating the effects of autocorrelated disturbances in the data, while n_2 introduces white noise directly to the output signal.

A comprehensive system identification procedure consists of experimental design and execution, data preprocessing, model structure selection and parameter estimation, and model validation. The following are emphasized in the tool:

Experimental design and execution. The success of any identification methodology hinges on the availability of an informative input/output data set obtained from a sensibly designed identification experiment. In *ITSIE*, deterministic, periodic signals relying on pseudo-random binary sequence (PRBS) and multisine inputs are considered. A PRBS is binary signal generated by using shift register modulo 2 addition. One cycle of a PRBS sequence is determined by the number of registers n_r and the switching time T_{sw}. The signal repeats itself after $N_s T_{sw}$ units of time, where $N_s = 2^{n_r} - 1$. The power spectral density for a PRBS signal is given by

$$\Phi_u(\omega) = \frac{a_{\rm mag}^2 (N_s+1) T_{sw}}{N_s} \left[\frac{\sin(\frac{\omega T_{sw}}{2})}{\frac{\omega T_{sw}}{2}} \right]^2, \qquad (3)$$

where $a_{\rm mag}$ is the magnitude of the PRBS signal.

Both direct parameter specification and applying time constant-based guidelines according to Rivera [1992] are evaluated in the tool. In practice, little is known about the process dynamics at the start of identification testing, and plant operating restrictions will discourage excessively long or very intrusive identification experiments. A guideline that provides a suitable estimate of the frequency band over which excitation is required is

$$\frac{1}{\beta_s \tau_{\rm dom}^H} \leq \omega \leq \frac{\alpha_s}{\tau_{\rm dom}^L}, \qquad (4)$$

where $\tau_{\rm dom}^H$ and $\tau_{\rm dom}^L$ are high and low estimates of the dominant time constant, and β_s is an integer factor representing the settling time of the process. For example, $\beta_s = 3$; specifies the low frequency bound using the 95% settling time ($T_{95\%}$) of the process. α_s, meanwhile, is a factor representing the closed-loop speed of response, written as a multiple of the open-loop response time.

Equation (4) is used to specify design variables in PRBS inputs. Expressions for specifying T_{sw} and n_r based on (4) are developed in Rivera [1992]:

$$T_{sw} \leq \frac{2.8 \tau_{\rm dom}^L}{\alpha_s}, \qquad (5)$$

$$N_s = 2^{n_r} - 1 \geq \frac{2\pi \beta_s \tau_{\rm dom}^H}{T_{sw}}. \qquad (6)$$

n_r and N_s are integer values, while T_{sw} is an integer multiple of the sampling time T. Increasing α_s and β_s will widen the frequency band of emphasis in the input signal and increase the resolution of the input signal spectrum. To reduce model variance it is beneficial to apply the highest input signal amplitude $a_{\rm mag}$ that operations will allow, and implement the PRBS input for the greatest number of cycles m possible. In practice, decisions regarding the magnitude of the input signal, spectral content, and experimental test duration are dictated by physical limitations, economics, and safety considerations, as noted by Ljung [1999].

Multisine signals are deterministic, periodic signals, represented in the single input case by the equation

$$u(k) = \lambda \sum_{i=1}^{n_s} \sqrt{2\alpha_i}\ cos(\omega_i k T + \phi_i) \qquad (7)$$

$$\omega_i = 2\pi i / N_s T, \quad n_s \leq N_s/2$$

The power spectrum of the multisine input

$$\Phi_u(\omega_i) = \left(\frac{\lambda^2 \alpha_i}{2} N_s \right) \quad i = 1, \cdots, n_s \qquad (8)$$

is directly specified through the selection of the scaling factor λ, the Fourier coefficients α_i, the number of harmonics n_s, and the signal length N_s. Equation (4) can also be used to specify design variables in multisine inputs, using guidelines found in Rivera et al. [1993]

$$N_s \geq \frac{2\pi \beta_s \tau_{dom}^H}{T} \qquad n_s \geq \frac{N_s T \alpha_s}{2\pi \tau_{dom}^L}. \qquad (9)$$

While the phase angles ϕ_i do not influence the power spectrum in a multisine, they do strongly influence plant-friendly metrics such as crest factor [Rivera et al., 2003]. Early work in the design of low crest factor multisines includes the work of Schroeder [1970], who derives a closed-form formula to select the phases in (7). The formula gives a reasonable result when the user-defined spectrum is flat and wideband, but under other conditions (bandlimited, in the presence of harmonic suppression, etc.) the results can be very undesirable. The deficiencies of Schroeder-phasing have motivated the need for more rigorous approaches, such as those involving optimization. A significant contribution in this regard is the successive p-norm approach by Guillaume et al. [1991], which is implemented in *ITSIE*.

Data preprocessing. Stationary data sets are generated in *ITSIE*, so only mean detrending is applied by default. Future versions of the tool will emphasize issues in prefiltering and control-relevance.

Model structure selection and parameter estimation. The general family of prediction-error models corresponds to

$$A(q)y(t) = \frac{B(q)}{F(q)}u(t-nk) + \frac{C(q)}{D(q)}e(t) \quad (10)$$

$$y(t) = \tilde{p}(q)u(t) + \tilde{p}_e(q)e(t) \quad (11)$$

where

$$A(q) = 1 + a_1 q^{-1} + \ldots + a_{n_a} q^{-n_a}$$
$$B(q) = b_1 + b_2 q^{-1} + \ldots + b_{n_b} q^{-n_b+1}$$
$$C(q) = 1 + c_1 q^{-1} + \ldots + c_{n_c} q^{-n_c}$$
$$D(q) = 1 + d_1 q^{-1} + \ldots + d_{n_d} q^{-n_d}$$
$$F(q) = 1 + f_1 q^{-1} + \ldots + f_{n_f} q^{-n_f}$$

The five most popular PEM models shown in Table 1 are evaluated in *ITSIE*, with FIR belonging as a subset of ARX models. The tool also includes PEM estimation of state-space models.

Method	$\tilde{p}(q)$	$\tilde{p}_e(q)$
ARX	$\frac{B(q)}{A(q)}q^{-nk}$	$\frac{1}{A(q)}$
ARMAX	$\frac{B(q)}{A(q)}q^{-nk}$	$\frac{C(q)}{A(q)}$
FIR	$B(q)q^{-nk}$	1
Box-Jenkins	$\frac{B(q)}{F(q)}q^{-nk}$	$\frac{C(q)}{D(q)}$
Output Error	$\frac{B(q)}{F(q)}q^{-nk}$	1

Table 1. Prediction-error model structures evaluated in *ITSIE*.

As noted in Ljung [1999], PEM estimation involves either linear and nonlinear regression, depending on the model structure being evaluated.

$$\arg \min_{\tilde{p},\tilde{p}_e} \frac{1}{N}\sum_{i=1}^{N} e^2(i) = \arg\min_{\theta} \frac{1}{N}\sum_{i=1}^{N}\left[y - \varphi^T(t|\theta)\theta\right]^2 (12)$$

The use of Parseval's Theorem enables a frequency-domain analysis of bias effects in PEM estimation that allows deep insights into the selection of design variables for these techniques. As the number of observations $N \to \infty$, the least-squares estimation problem denoted by (12) can be written as:

$$\lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} e^2(t) = \frac{1}{2\pi}\int_{-\pi}^{\pi} \Phi_e(\omega)d\omega \quad (13)$$

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

$$\Phi_e(\omega) = \frac{1}{|\tilde{p}_e(e^{j\omega})|^2}\left(|p^*(e^{j\omega}) - \tilde{p}(e^{j\omega})|^2\Phi_u(\omega) + |p^*(e^{j\omega})|^2\sigma_{n_1}^2 + \sigma_{n_2}^2\right) \quad (14)$$

Equation (14) helps explain systematic bias effects in identification, which are readily explored by the *ITSIE* tool. 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 different magnitudes of the noise variances $\sigma_{n_1}^2$ and $\sigma_{n_2}^2$.

Model validation. In *ITSIE*, model validation consists principally of classical methods of simulation, crossvalidation, residual analysis on the prediction errors, and step responses. To enhance its educational value, the step response of the true plant is presented alongside that generated by the estimated models. The percent of the output variance explained by each model on the crossvalidation data set is also reported.

Leveraging the interplay between the various stages of the identification problem is readily supported in *ITSIE*. One example is ARX estimation, where model structure selection can be accomplished without substantial user intervention through the sensible use of crossvalidation. Because ARX parameter estimation consists of solving a linear least squares problem, a large number of model structures defined by ranges for n_a, n_b and n_k can be evaluated without incurring significant computational burden. The model order that minimizes the loss function over a crossvalidation data set can be obtained without iteration.

3. INTERACTIVE TOOL DESCRIPTION

This section briefly describes the functionality of the developed tool, which highlights the theoretical concepts described in the previous section. The tool is freely available through `http://aer.ual.es/ITSIE/` [Guzmán et al., 2008a] and can be used in Windows, Mac, and Linux operating systems without the need for a Sysquake license. One consideration that must be kept in mind is that the tool's main feature - interactivity - cannot be easily illustrated with written text. Nonetheless, some of the features and advantages of the application are shown below. The reader is cordially invited to download the tool and personally experience its interactive features.

When developing a tool of this kind, one of the most important things that the developer needs to keep in mind is the organization of the main windows and menus to facilitate to the user an understanding of the identification technique [Dormido, 2004, Guzmán, 2006]. The main window of the tool is divided into several sections represented in Figures 1 and 2. The graphical distribution has been performed according to the most important steps in a system identification process, described as follows:

- *Plant definition and simulation parameters.* The central part of the tool has a section called Simulation parameters, which allows interactively modifying the noise sources of the fifth-order plant from Equations (1) and (2). Two sliders are available. The first one, noise 1, allows modifying the noise source $n_1(t)$ and the second one, noise 2, is used to change the noise source $n_2(t)$. On the other hand, other simulation parameters, such as sampling time, are available from an entry at the Parameters menu. Notice that the sampling time can be also modified from the Input signal graphic by dragging on the red vertical line.
- *Input design.* A parameter definition section and three interactive graphics characterize the input design stage. The parameter definition section is called Input signal parameters, being located at the top of the middle section of the tool. The three graphics are located at the right-hand side of the tool, namely, Input signal, Autocorrelation, and Power Spectrum, representing one cycle of the input signal, the input signal autocorrelation, and the input signal power spectrum, respectively (see Figure 1). From the Input

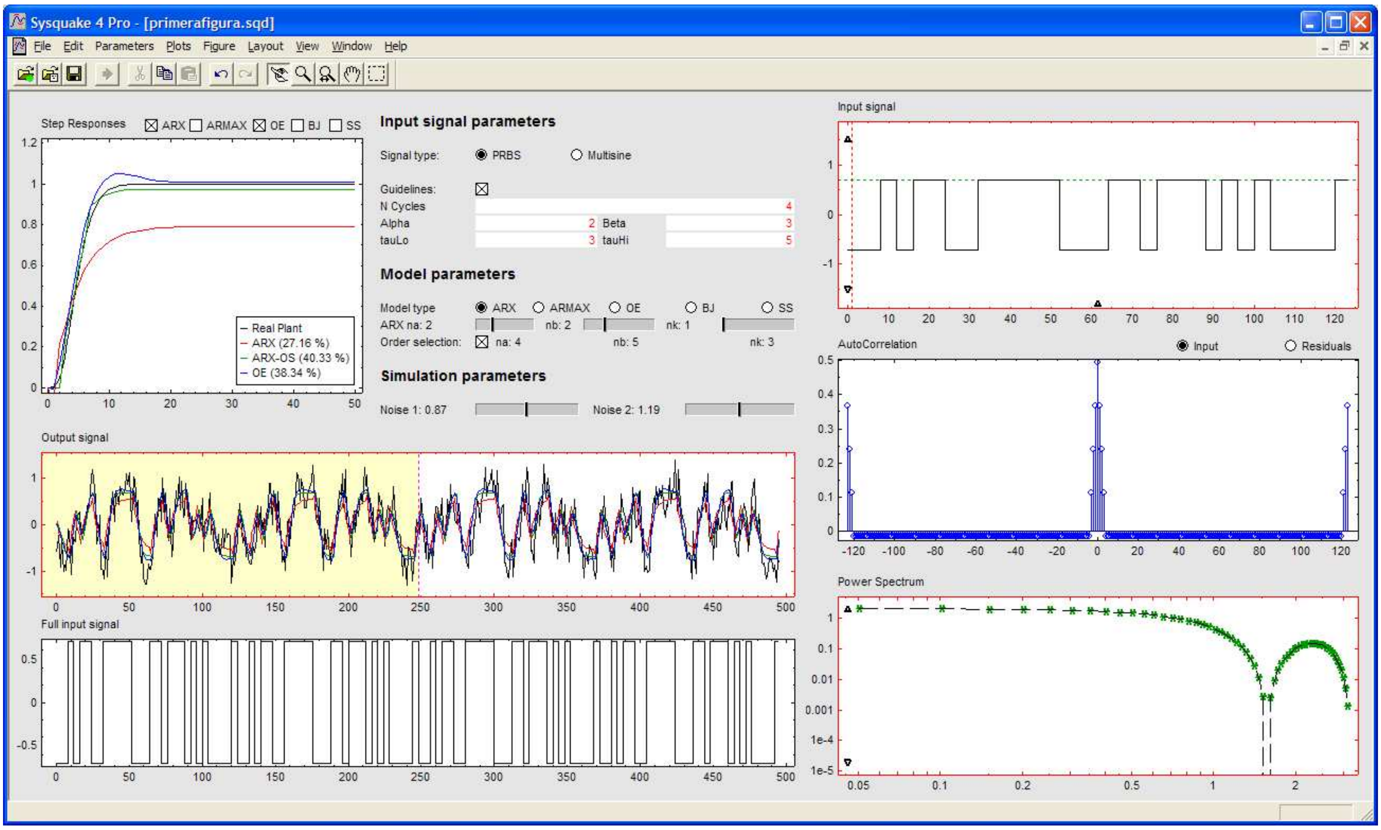

Fig. 1. *ITSIE* interactive tool user interface demonstrating four cycles of a PRBS input (autocorrelation shown) based on application of the Section 2 time-constant guidelines. ARX-[2 2 1] and OE-[2 2 1] models are compared with an ARX-[4 5 3] model obtained from exhaustive analysis of model orders on a crossvalidation data set.

signal parameters area, the user can choose the type of the input signal (PRBS as shown in Figure 1 or multisine as shown in Figure 2) and whether to use the checkbox called Guidelines to decide between specifying the input signal directly or following the guidelines mentioned in Section 2. When the user does not select the guidelines, that is, the Guidelines checkbox is not active, the input signal parameters can be interactively modified using specific sliders or dragging on the graphics. For instance, if the PRBS is selected (such as shown in Figure 1), 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 same time, from the Input signal graphic, it is possible to modify the switching time dragging on the magenta vertical line, the signal amplitude using the green horizontal line, and the number of cycles dragging on the small black triangle located at the x-axis. Furthermore, the number of registers and the switching time can be changed from the Power Spectrum graphic using the green vertical lines. The user can rely on these interactive features to understand the influence of input signal parameters from different points-of-view.

- *Model structure selection and parameter estimation.* On top of the Step responses graphic, located on the upper left-hand side of the tool, there is a set of checkboxes allowing to active the different model structures, namely, ARX, ARMAX, OE, BJ, and SS. Once a model structure is selected, the estimation and validation results for that model are shown in corresponding parts of the tool. Below the Input signal parameters section there is an area called Model parameters showing parameters to modify the orders of the different model structures. Several radio buttons are available to choose between the different model structures. Once a model structure is selected, different sliders appear making it possible to modify the associated orders interactively. For instance, if an ARX model is chosen, sliders representing n_a, n_b, and n_k are shown. Furthermore, for the case of the ARX model structure, a checkbox is displayed to activate the automatic order selection mode using crossvalidation, as described in Section 2. By default, the parameter ranges are set to $n_a = 1...10$, $n_b = 1...10$, and $n_k = 1...10$, but these limits can be changed from the Parameters menu.

Once a input signal has been configured, the final input with all the desired cycles is shown in a graphic called Full input signal, which is located at the lower-left corner of the tool. This full input signal is applied to the fifth-order plant with noise 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 and validation process. In the Output signal graphic, an interactive magenta vertical line defines the estimation and validation data sets. The area shown in yellow (at the left of the vertical line) specifies the estimation data, whereas

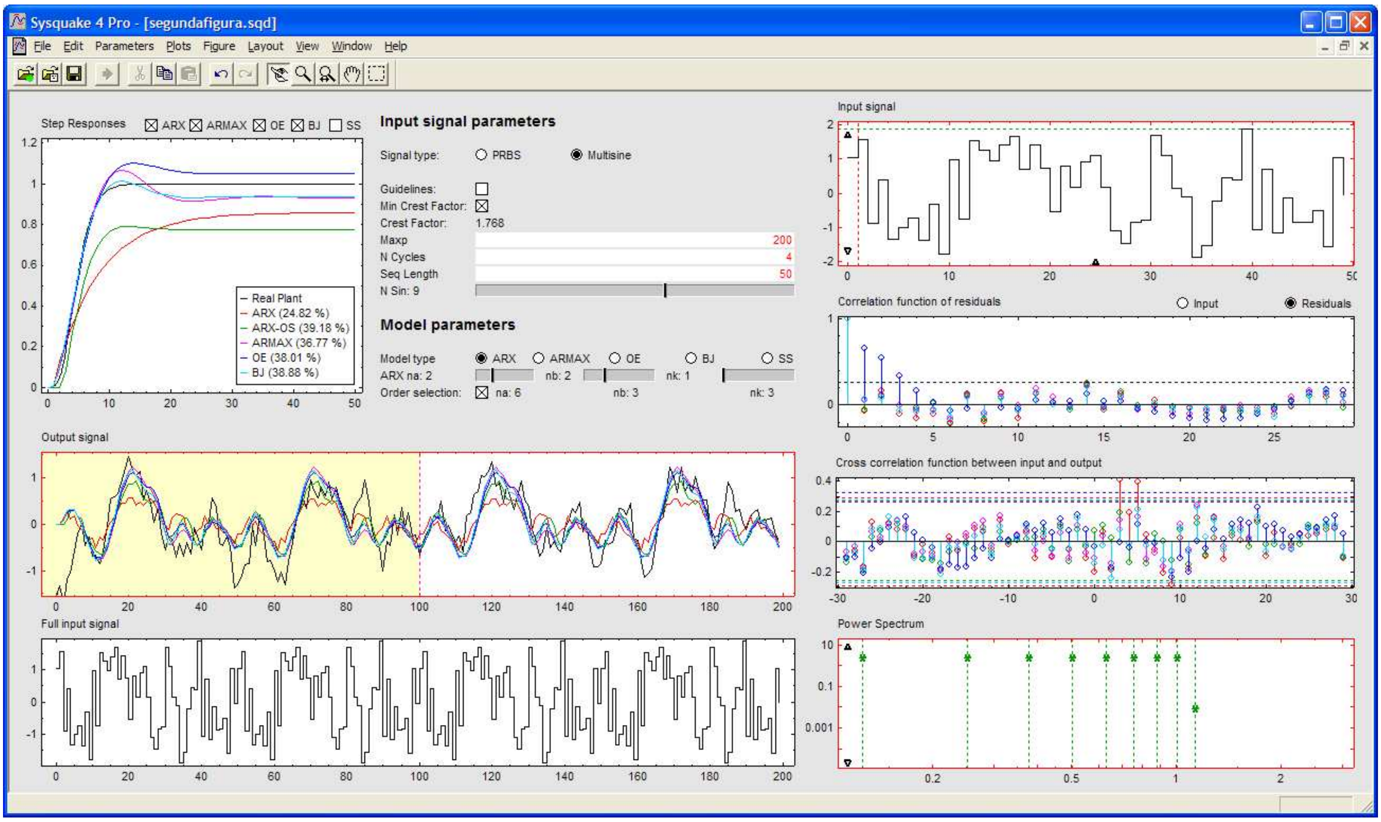

Fig. 2. *ITSIE* interactive tool user interface depicting four cycles of a minimum crest factor multisine input with phases per Guillaume et al. [1991] from directly specified signal parameters. Model estimates for ARX, ARMAX, OE, and Box-Jenkins estimation are shown along with residual analysis of the prediction errors.

the white area represents the validation data (at the right side of the vertical line). Therefore, when a model structure is selected, this 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 fifth-order system. Different colors are used to distinguish between signals, black for the original data of the fifth-order system, red for ARX, green for ARX with order selection, magenta for ARMAX, blue for OE, cyan for BJ, and orange for SS. These colors are consistently used in different parts of tool to refer to the model results. Clicking on the Output signal graphic will generate a fresh realization of the noise sequences n_1 and n_2, enabling the user to interactively experience variability in the estimates resulting from the stochastic nature of the disturbance.

- *Model validation.* As mentioned in the previous bullet, 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 three different graphics: Step responses, Correlation function of residuals, and Cross correlation function between input and output. For all these graphics, the same color distribution noted before is used to represet the results of each model. The Step responses graphic, which is located at the upper left-hand side of the tool, shows the step responses for the each resulting model and a legend representing its goodness of fit in %. On the other hand, Correlation function of residuals and Cross correlation function between input and output graphics, located between the Input signal and Power spectrum graphics, describe the auto- and cross-correlation between the input signal and the prediction-error for each model. By default, the input Autocorrelation graphic is shown instead of these two graphics. In order to switch between the input autocorrelation and residual analysis, two radio buttons are shown below the Input signal graphic that enable this commutation.

The interactive tool provides the user with multiple degrees of freedom for understanding the theoretical concepts and impact of choices made in the different steps on the system identification process. The main advantage with respect to other existing software tools is that the most important stages on system identification are shown simultaneously in one screen (input design, model structure selection, parameter estimation, and validation), and that the interactive features of the tool allow the user to understand and experience the relationships between these different stages, the meaning and effects of the associated parameters, and the bidirectional interpretation between parameter modifications from numerical (using sliders) and graphical (using interactive elements on the graphics) points of view.

4. ILLUSTRATIVE EXAMPLES

We have noted that there are large numbers of possible scenarios with educational value that can be illustrated by the *ITSIE* tool. The list below is by no means exhaustive, but representative of some valuable concepts:

(1) The importance of selecting crossvalidation data, and how it impacts parameter estimation, particularly the effectiveness of automated order selection in ARX estimation.
(2) A comparison between two different input signal types (i.e., PRBS versus multisines) and the usefulness of crest factor minimization for achieving "plant-friendliness" [Rivera et al., 2003].
(3) Understanding the issue of persistent excitation, as displayed in the interrelationship between input design and model order selection. This is particularly useful when using the multisine input signal, given that the user can directly specify the number of nonzero harmonics in this signal.
(4) The importance of taking advantage of *a priori* knowledge in input design. The time-constant guidelines presented in Section 2 can be thoroughly evaluated and appreciated.
(5) The relative merits of various validation criteria. Correlation analysis on the residuals may indicate that there is still a need to refine on model structure; however, the model may still describe a large percentage of the output variance in the validation data and closely match the plant step response.

Figures 1 and 2 depict two interesting cases evaluated with the tool. Figure 1 presents the use of a PRBS signal designed using the guidelines in Section 2. Four cycles of data are generated, with two used for estimation, and two used for validation purposes. ARX-[2 2 1] and OE-[2 2 1] models are evaluated in this case, with the OE-[2 2 1] model showing a much closer fit to the true step response as a consequence of having an independently parametrized noise model, which reduces bias. The order selection feature recommends an ARX-[4 5 3] model structure, which has the best fit of any of the evaluated models.

In Figure 2 a minimum crest factor multisine input with user-specified parameters but phases chosen according to the algorithm by Guillaume et al. [1991] is evaluated. Nine harmonics are specified by the user, with the ability to adjust each amplitude interactively. Residual analysis for ARX, ARMAX, Output Error, and Box-Jenkins estimation is shown, with the need to improve model structure in the ARX-[2 2 1] model clearly depicted.

5. CURRENT AND FUTURE PLANS

The first official use of *ITSIE* in a classroom setting was as part of a system identification short course taught at the University of Almería in September, 2008. The tool was warmly received by students. It is being extensively used as part of ChE 494-598: Introduction to System Identification, a combined undergraduate-graduate level course being taught at Arizona State University in spring 2009. Detailed reports of the experience with the tool will be made during the SYSID 2009 meeting in July.

This paper has focused on one member of a family of interactive tools for system identification envisioned by the authors. Extensions to the current tool consist of expanding the range of plants that can be evaluated and enabling students to import their own data. Future tools will examine the interplay between input design, data prefiltering, and model structure on control-relevance, as well as tradeoffs in closed-loop identification and issues in multivariable system identification.

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