Interactive Closed-Loop System Identification Using *ITCLI*

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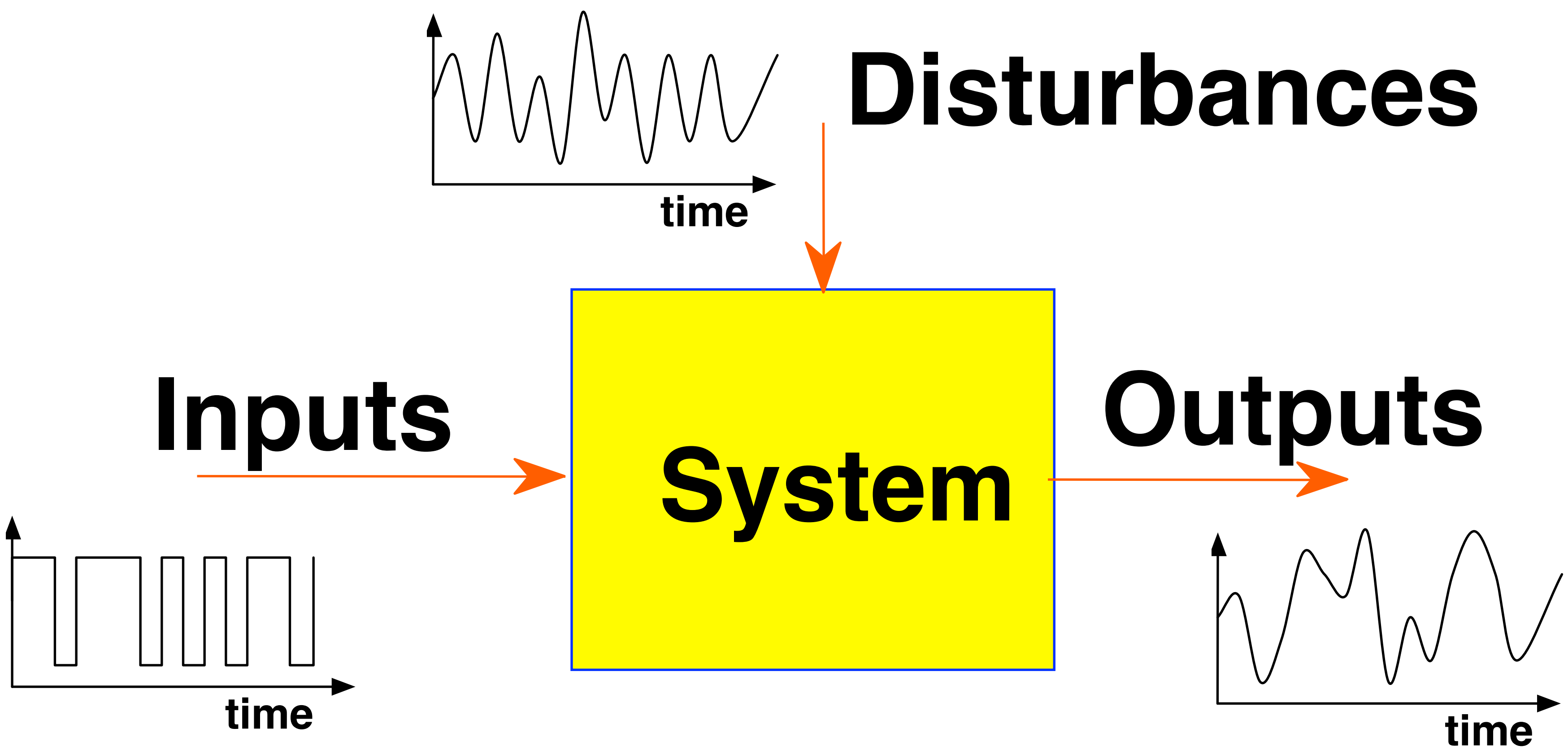
Outline

- What is system identification?
- Basic problems in closed-loop system identification.
- Understanding bias and variance in closed-loop system identification using prediction error methods.
- Some example problems; *I*nteractive *T*ool for *C*losed-*L*oop *I*dentification (*ITCLI*) illustration.
- Summary and conclusions.

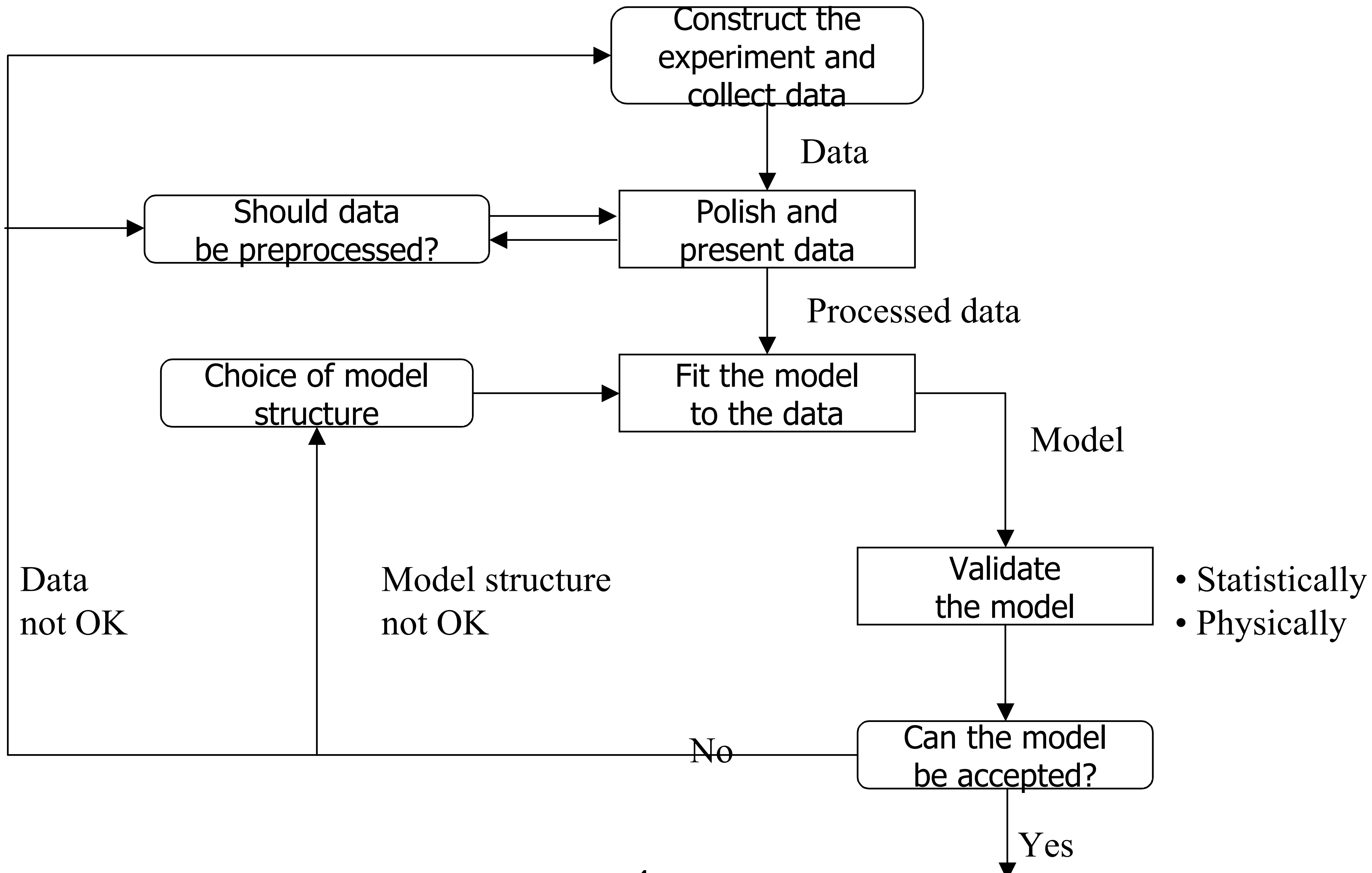
System Identification



- "Identification is the determination of on the basis of input and output, of a system within a specified class of systems to which the system under test is equivalent." - *Lofti Zadeh, 1962.*
- System identification focuses on the modeling of dynamical systems from experimental data.

System Identification Loop (Ljung and Glad, 1994)

- System identification is an inherently iterative procedure; however, some iterations are more expensive (and demanding) than others.



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MATLAB System Identification Toolbox

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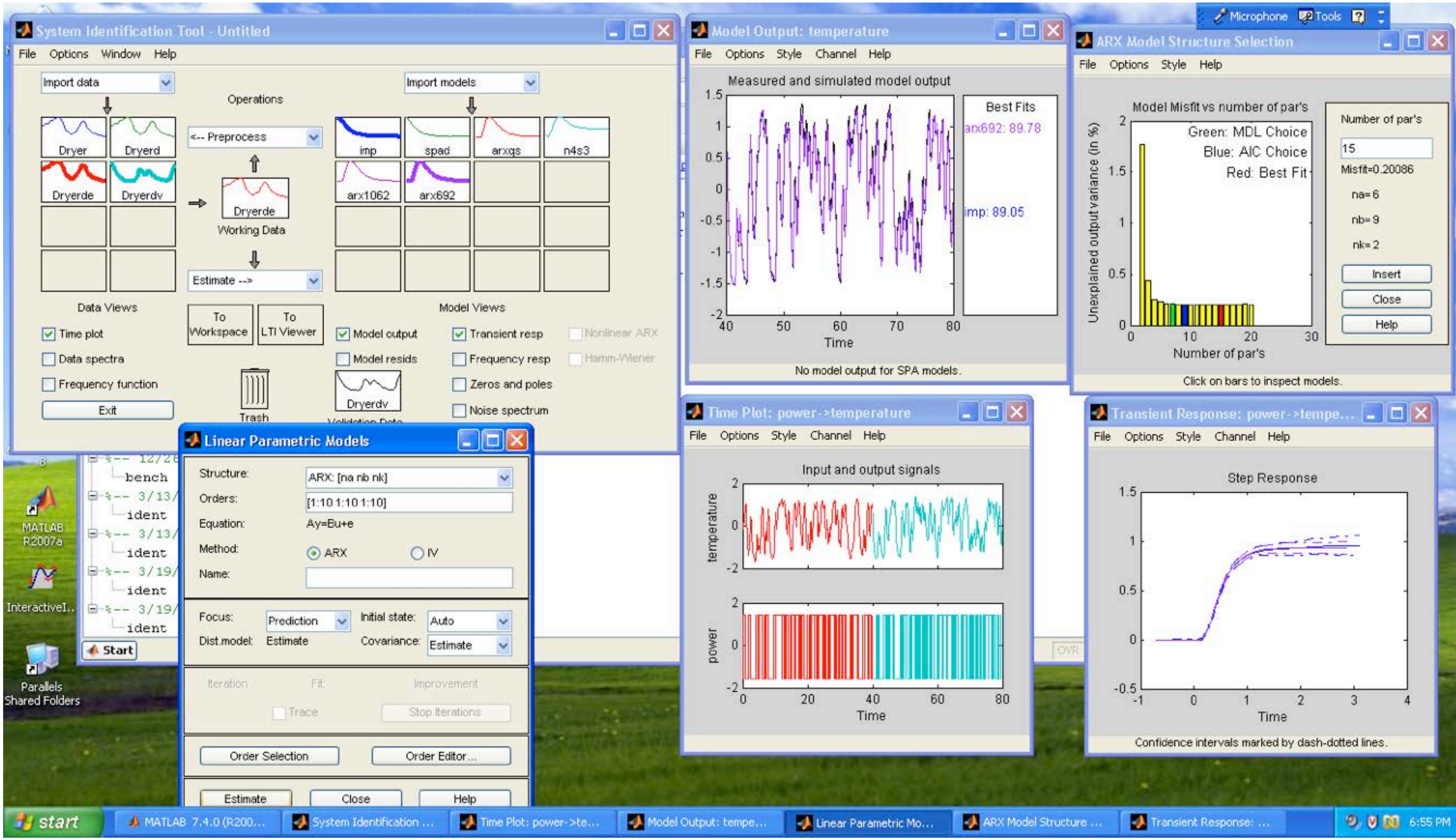
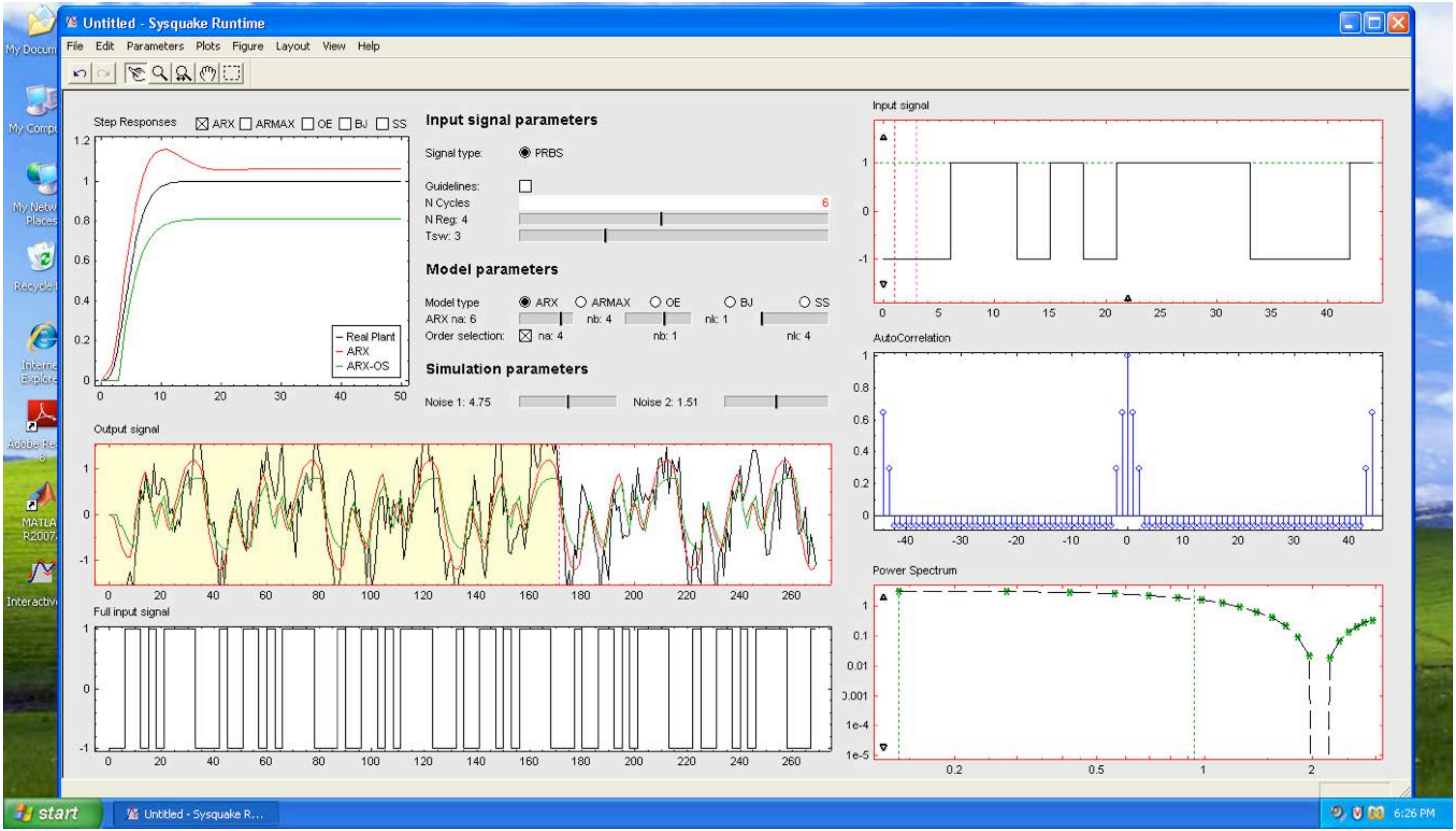


ident Graphical User Interface shown; command-line functionality also available.

Interactive Tool for System Identification Education (*ITSIE*)



Written using Sysquake (www.calerga.com) in collaboration with Professors José Luis Guzmán and Manuel Berenguel Soria (Univ. of Almería, Spain) and Sebastián Dormido Bencomo (UNED, Spanish National Distance Learning University, Madrid). Paper in *Advances in Engineering Software.*

Interactive Tool for Control-Relevant Identification (*ITCRI*)

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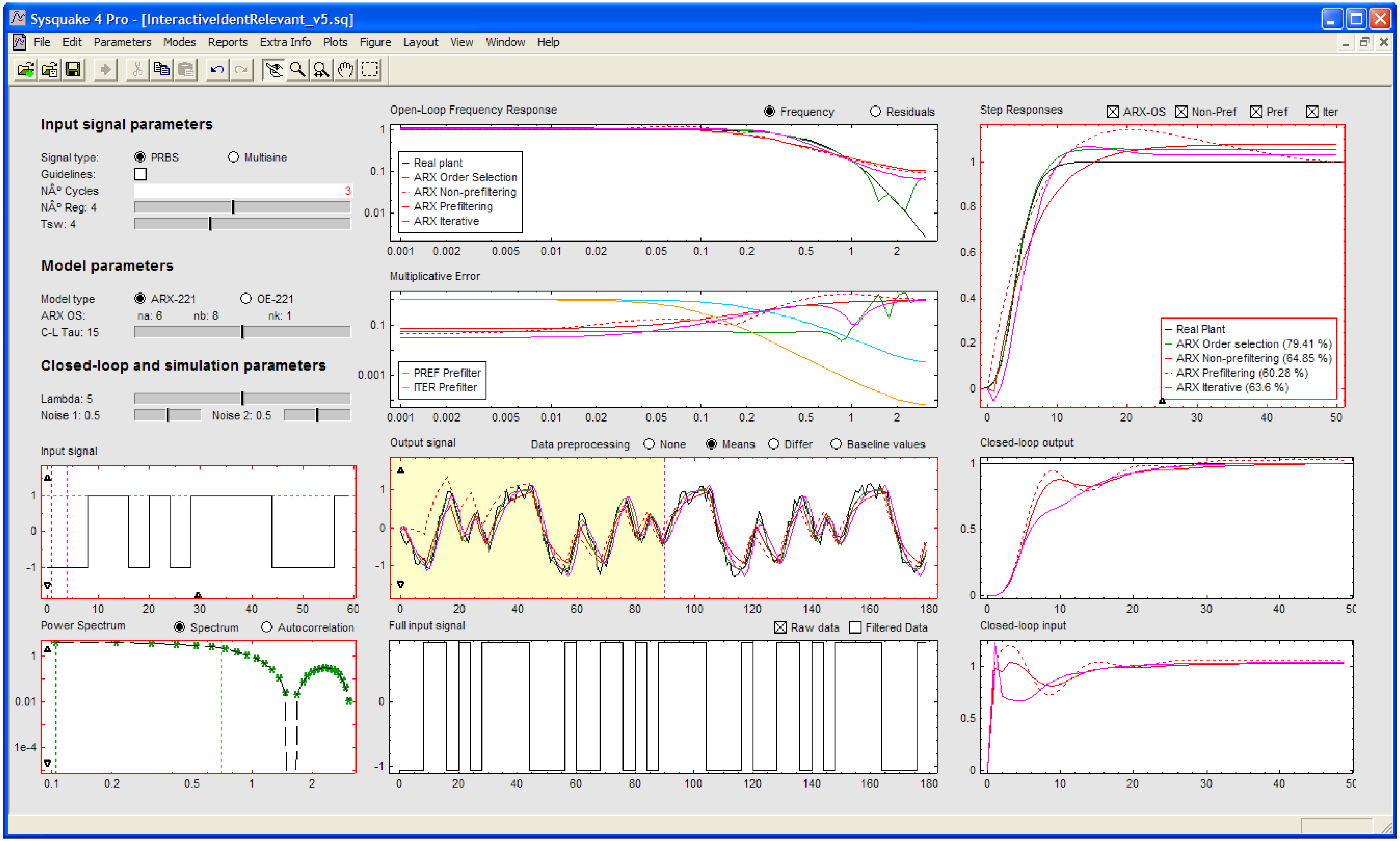

- Interactive Tool for Control-Relevant Identification (*ITCRI*), developed by Álvarez, Guzman, Rivera, Dormido, and Berenguel. Paper published in *Control Engineering Practice*.

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i-pIDtune

(Tool for integrated system ID and IMC-PID control)

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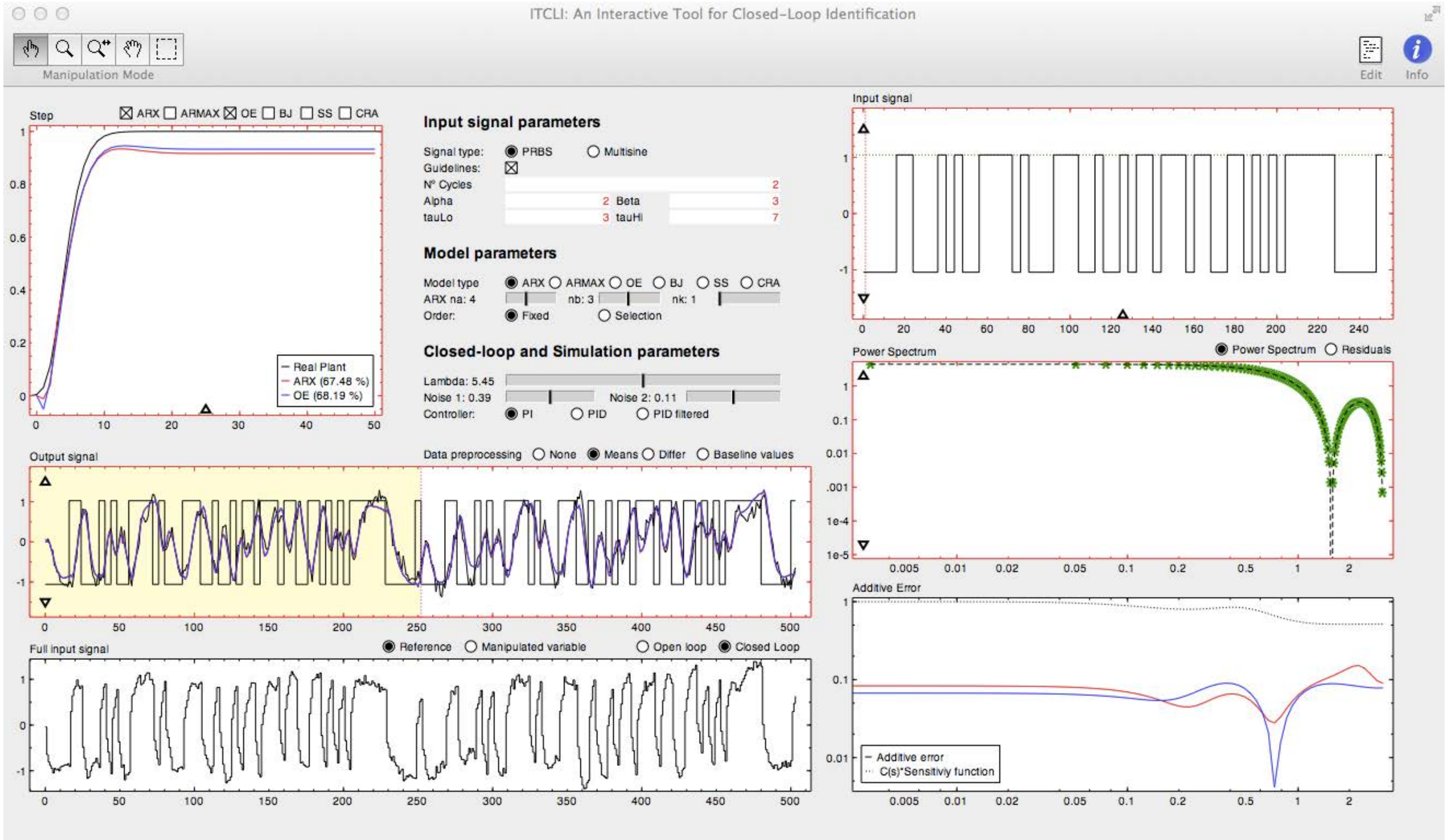
- Presented at PID'12, Brescia, Italy.

Interactive Tool for Closed-Loop Identification (*ITCLI*)



- To be presented at the 2014 IFAC World Congress, Cape Town.

Textbook Under Preparation

Understanding System Identification

An Interactive, Control-Relevant Exploration

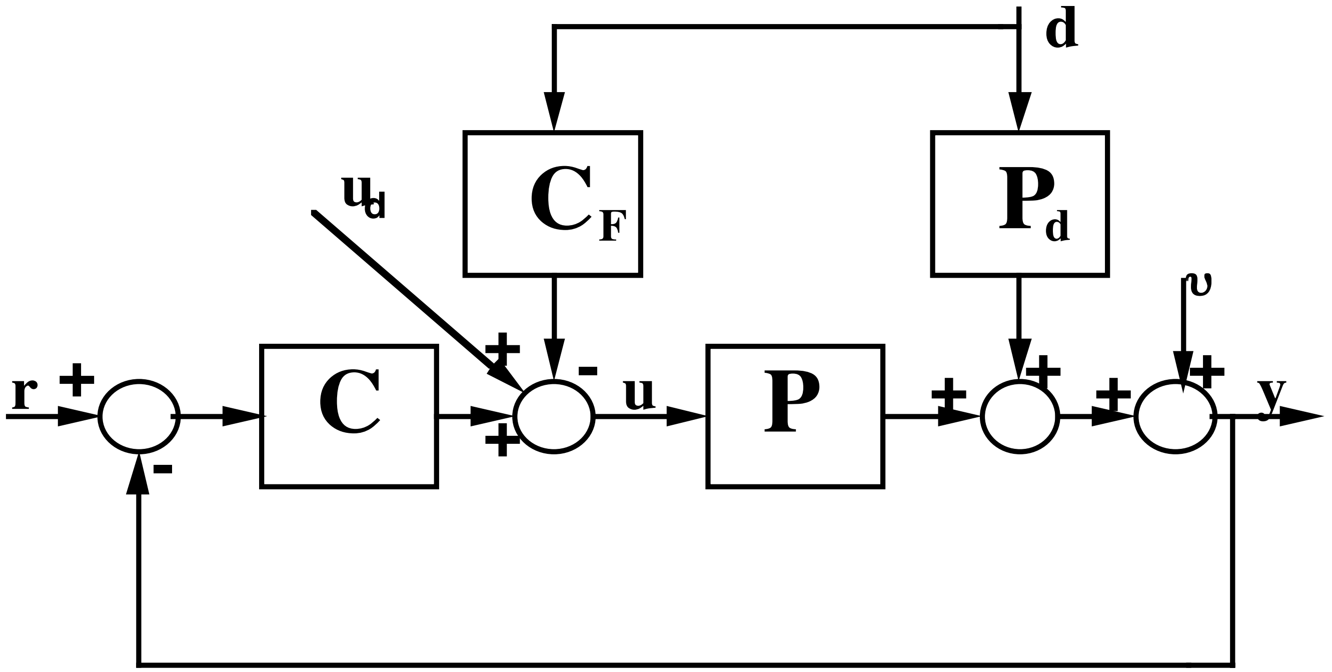
Daniel E. Rivera
José Luis Guzmán
Manuel Berenguel
Sebastián Dormido

Motivation for Closed-Loop Identification

- Eliminates the need to put the control loop on “manual” during identification testing.
- Makes it possible to perform identification while keeping the plant within operating limits.
- Enables “plant-friendly” identification of open-loop unstable systems.

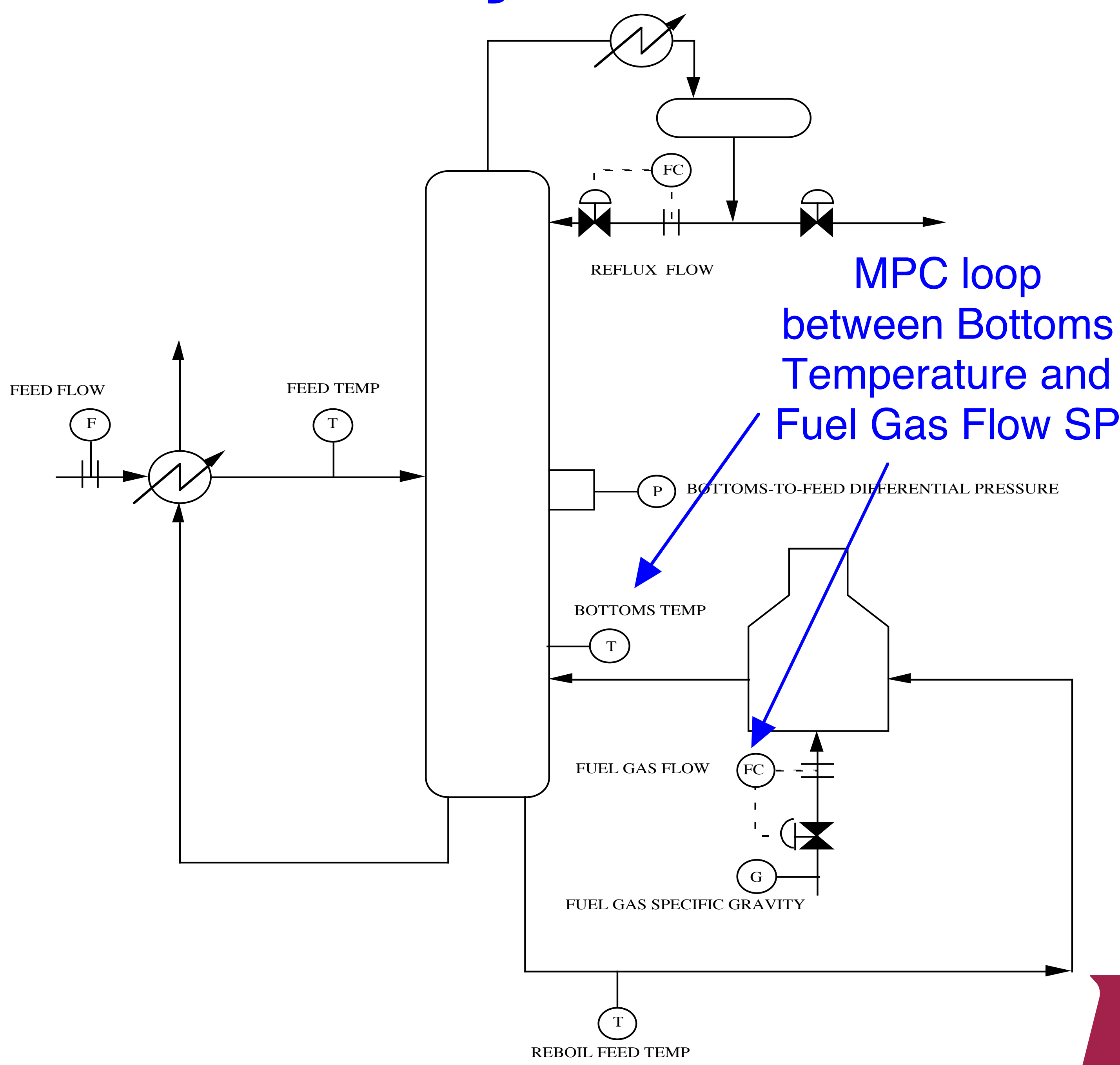
Closed-loop identification does not necessarily imply “something for nothing”

Problems in Closed-Loop Identification



- crosscorrelation will exist between disturbance (d) and input (u) as a result of the control
- control action will introduce additional bias by "eating away" at excitation

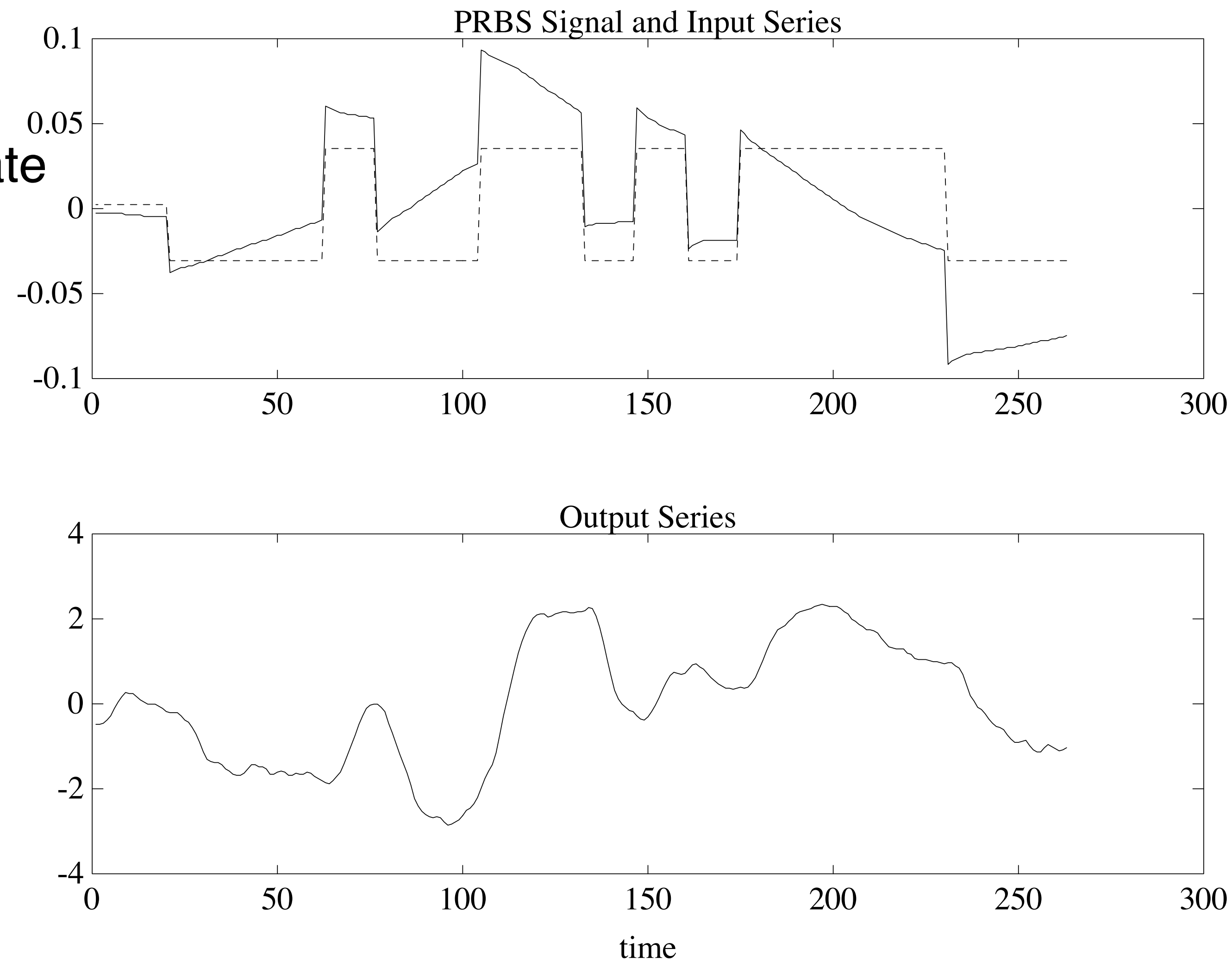
Refinery Debutanizer



Debutanizer Closed-Loop Testing

Fuel Gas Flowrate Setpoint

Bottoms Temperature



Closed-loop data set generated by signal injection at the Fuel Gas Flowrate Setpoint; dashed line shows external signal (ud); solid lines show u and y, respectively

Ljung's Thoughts:

From "Identification in Closed Loop: Some Aspects on Direct and Indirect Approaches," invited paper for SYSID '97, Fukuoka, Japan.

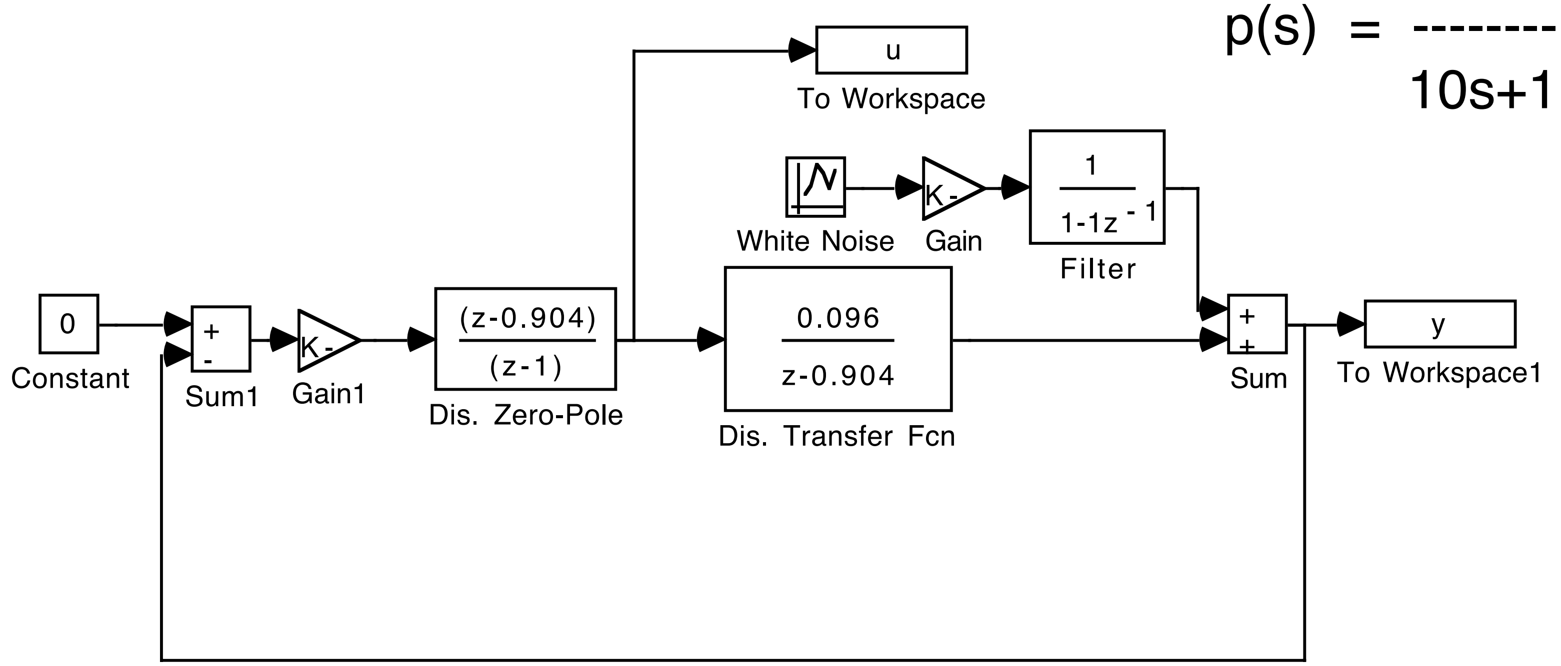
- *"... the basic problem in closed-loop identification (is this): the purpose of feedback is to make the sensitivity function small, especially at frequencies with disturbances and poor system knowledge. Feedback will thus worsen the measured data's information about the system at these frequencies."*

- There are no difficulties, per se, with closed-loop data; simply that in practical use, the information content is less

- One could make closed-loop experiments with good information contents (but poor control performance)

Why closed-loop data can be bad for system identification

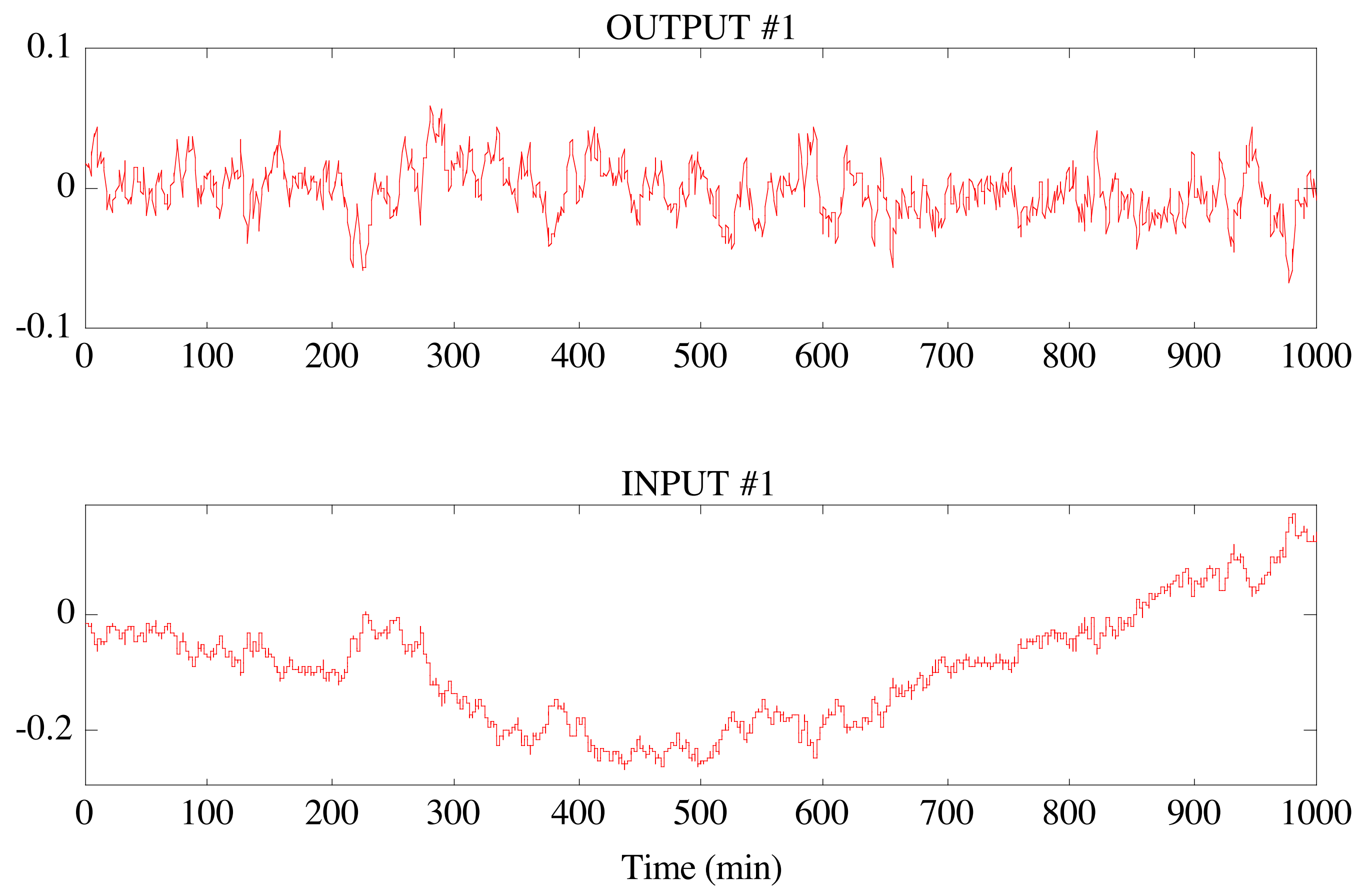
$$p(s) = \frac{1}{10s+1}$$



- Consider a first-order system controlled by a discrete-time PI controller subject to nonstationary random disturbance.

- Input/output data (y,u) from this control system is used to fit a Finite Impulse Response model (order 50).

Closed-loop identification data



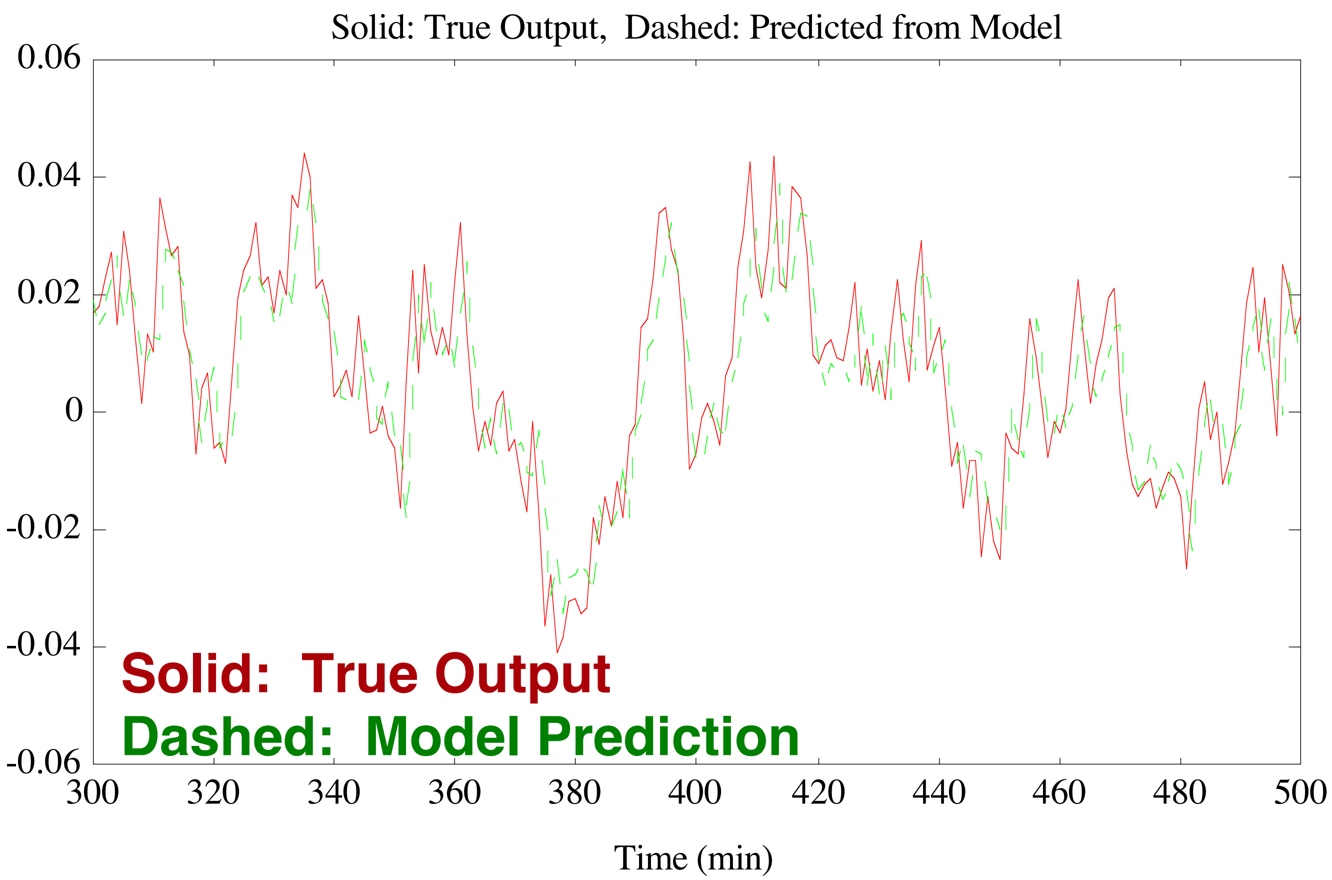

```
>> th = arx([y  u],[0 50 1]);
```

Finite Impulse Response (FIR)

$$y(t) = B(q)u(t - nk) + e(t)$$
$$B(q) = b_1 + b_2 q^{-1} + \cdots + b_{n_b} q^{-n_b+1}$$

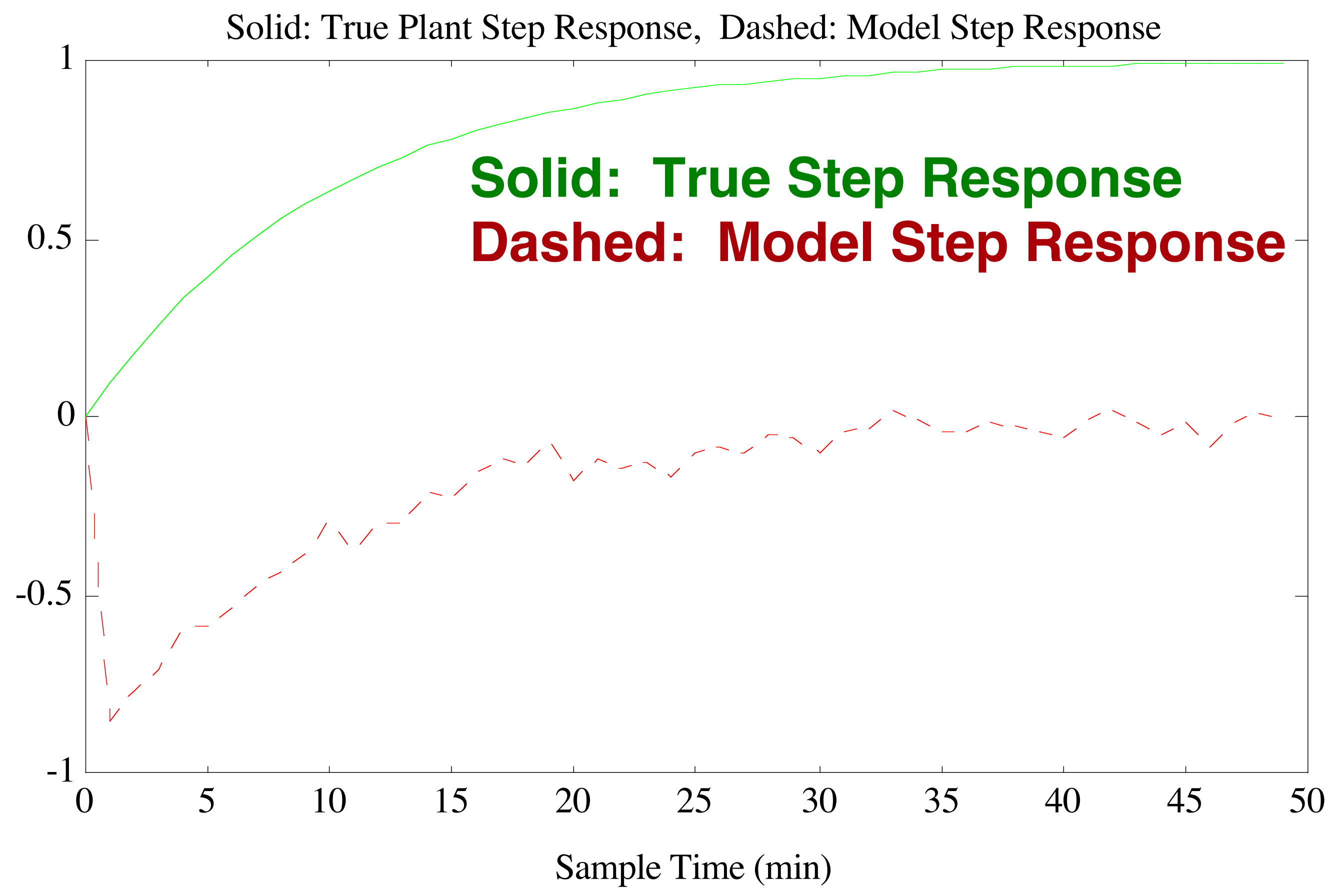
- Model representation similar to correlation analysis (CRA).
- Estimation is a linear regression problem.
- Because of fast sampling, *nb* is usually of high order (20 coefficients or more)
- Noise model is unity (i.e., no autocorrelated noise model is supported in FIR estimation)

Model Simulation - Closed-loop Data




```
>> ysim = idsim(u,th)
>>plot([y  ysim])
```

Model Step Response



Conclusion: the closed-loop data set (as presented) is not informative for system identification.

Practical Considerations in Closed-Loop Identification

1. How does one generate an informative data set for identification when the plant is in the closed-loop?

2. What is the most appropriate signal injection point?

3. How should the controller be tuned for c-l identification ?

4. What are the best model structures/parametrizations for c-l identification?

5. How can design variables (i.e., prefiltering) improve the results of c-l identification?

Closed-Loop Identification Schemes

- *Direct Approach:* Apply prediction-error methods to (y,u) the same way as in open-loop operation ignoring possible feedback and not using the external signals (r or ud)

- *Indirect Approach:* Identify the closed-loop system between the external signal and the output (which is in effect an open-loop system); retrive the plant from this estimate, making use of the known controller transfer function.

Basic Issues in Closed-Loop System Identification

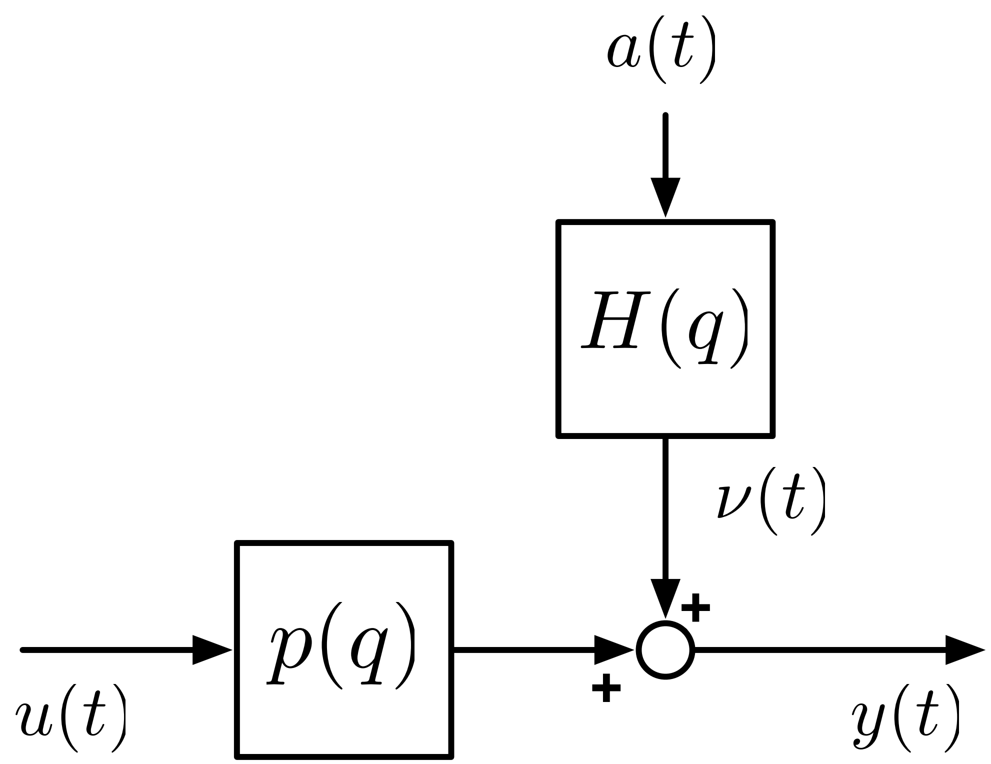
"Identifiability" (*Soderstrom et al, 1976, Gustavsson et al., 1977*) Two types of identifiability conditions exist:

• System Identifiable (SI). Data is informative for certain model structures if an external input is not entered into the loop.

• Strong System Identifiable (SSI). Needs an external signal or changing controllers to obtain an informative data set.

SSI is the most desirable condition, since prediction-error methods can be applied without modification.

"Accuracy" Error caused by bias and variance issues (e.g., choice of model structure, input signal magnitudes and excitation, presence of noise, number of model parameters, duration of experimental test)



$$\begin{aligned} \text{True Plant:} \quad y(t) &= \quad p(q)u(t) + H(q)a(t) \\ \text{Plant Model:} \quad y(t) &= \quad \tilde{p}(q)u(t) + \tilde{p}_e(q)e(t) \end{aligned}$$

- Assume that $y(t)$, $u(t)$, and $\nu(t)$ are stationary (or "quasi-stationary") as before. $a(t)$ is white noise;
- Our goal is to obtain $\tilde{p}(q)$ and $\tilde{p}_e(q)$ as estimates for $p(q)$ and $H(q)$, respectively.
- $\tilde{p}_e(q)$ is commonly referred to as the "noise" model. $e(t) = y(t) - \hat{y}(t|t-1)$ is the one-step-ahead prediction error.

Understanding Bias

$$\begin{aligned} \text{True Plant:} \quad y(t) = &\quad p(q)u(t) + H(q)a(t) \\ \text{Plant Model:} \quad y(t) = &\quad \tilde{p}(q)u(t) + \tilde{p}_e(q)e(t) \end{aligned}$$

Consider prefiltered input/output data

$$y_F(t) = L(q)y(t) \qquad u_F(t) = L(q)u(t)$$

Asymptotically (as the number of observations $N \rightarrow \infty$), the least-squares estimation problem can be written as:

$$\min_{\tilde{p},\tilde{p}_e} \lim_{N\rightarrow\infty} \frac{1}{N} \sum_{i=1}^{N} e_F^2(t) = \min_{\tilde{p},\tilde{p}_e} \frac{1}{2\pi} \int_{-\pi}^{\pi} \Phi_{e_F}(\omega) d\omega$$

where Φ_{e_F}, the prefiltered prediction-error spectrum is

$$\Phi_{e_F}(\omega) = \frac{|L(e^{j\omega})|^2}{|\tilde{p}_e(e^{j\omega})|^2} \left(|p - \tilde{p}|^2 \Phi_u(\omega) + 2\mathrm{Re}\left((p - \tilde{p})H^*(e^{j\omega})\Phi_{ua}(\omega)\right) + |H(e^{i\omega})|^2 \sigma_a^2\right)$$

Understanding Bias (Continued)

$$\Phi_{e_F}(\omega) = \frac{|L(e^{j\omega})|^2}{|\tilde{p}_e(e^{j\omega})|^2}\left(|p-\tilde{p}|^2\Phi_u(\omega) + 2\mathrm{Re}\left((p-\tilde{p})H^*(e^{j\omega})\Phi_{ua}(\omega)\right) + |H(e^{i\omega})|^2\sigma_a^2\right)$$

Input signal power $\Phi_u(\omega)$**.** The input signal must have sufficient power over the frequency range of importance to the control problem.

Choice of prefilter $L(q)$**.** The prefilter acts as a frequency-dependent weight on the estimation problem that can be used to influence the goodness of fit in selected portions of the model's response.

Structure of $\tilde{p}$**.** Expanding the model set (e.g. by increasing model order) decreases bias.

Structure of $\tilde{p}_e$**.** Can act as a weight similar to prefiltering, and potentially introduce undesirable bias if not properly specified. Autoregressive terms ($A(q)$ or $D(q)$) will emphasize the goodness-of-fit at high frequencies.

Noise spectrum $\Phi_\nu(\omega) = |H(e^{j\omega})|^2\sigma_a^2$**.** If noise dynamics differ substantially from plant dynamics, a trade-off between fitting to $\tilde{p}$ and fitting to $\tilde{p}_e$ will result whenever $A(q) \neq 1$.

Crosspectrum $\Phi_{ua}(\omega)$**.** Correlation between the input and disturbance (as a result of closed-loop operation or operator intervention) may result in bias.

Consistent PEM estimation

Consistent prediction-error estimation, i.e., as $N \to \infty$

$$\min_{\tilde{p},\tilde{p}_e} \lim_{N\to\infty} \frac{1}{N} \sum_{i=1}^{N} e^2(t) = \sigma_a^2$$

$$\tilde{p}(q) \to p(q) \qquad \tilde{p}_e(q) \to H(q) \quad \text{with probability 1}$$

is achieved when the following are true:

1. *The model structure for $\tilde{p}(q)$ and $\tilde{p}_e(q)$ describes the true plant.* A suitable model structure must be selected.

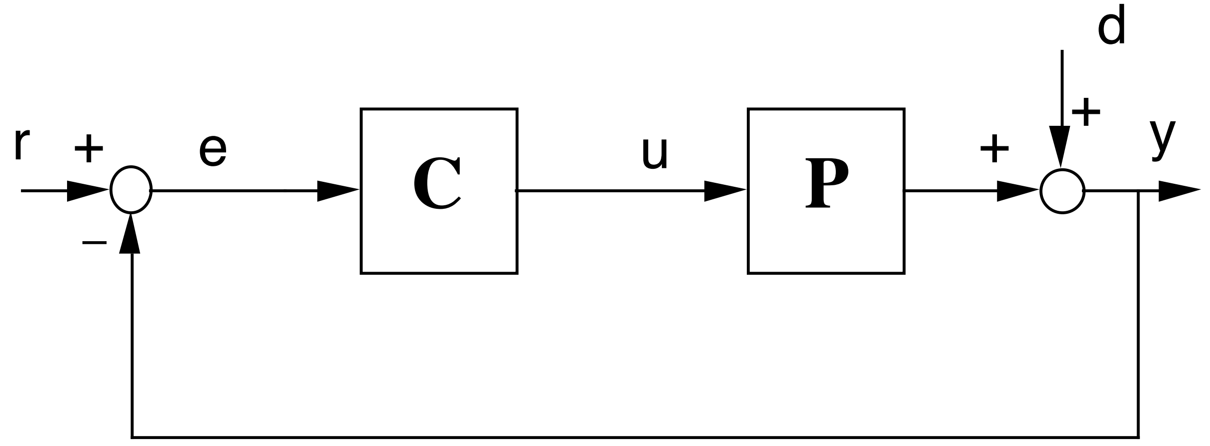
2. *$u(t)$ shows persistent excitation.* The autocovariance matrix Γ_u for the input signal $u(t)$ must be of full rank for dimensions corresponding to the order of the models $\tilde{p}$ and $\tilde{p}_e$. An equivalent statement is that the power spectrum of $u(t)$ have nonzero power $(\Phi_u(\omega) \neq 0)$ over the number of frequencies corresponding to the model order.

Note: The theory does not require $u(t)$ and $a(t)$ to be uncorrelated sequences (i.e., $\rho_{ua}(k) = 0$ for all k); however, if the input and the disturbance are uncorrelated, $p(q)$ can be consistently estimated by $\tilde{p}(q)$ despite an erroneous model structure for $\tilde{p}_e(q)$. This has practical benefits.

Caveats for Closed-Loop Data

- Consistent estimation of p(z) requires correct knowledge of both the plant and noise model structure (unlike consistent estimation under open-loop conditions with uncorrelated input and disturbance, which allows for an erroneous noise model).
- a "perfect" fit to closed-loop or correlated data may result from an erroneous model
- Information contents of the data affected by the presence of feedback (we will examine this in greater detail later).
- The asymptotic variance of estimated models generally increases under closed-loop conditions in comparison with open-loop (Gevers, Ljung, Van den Hof, 2001)

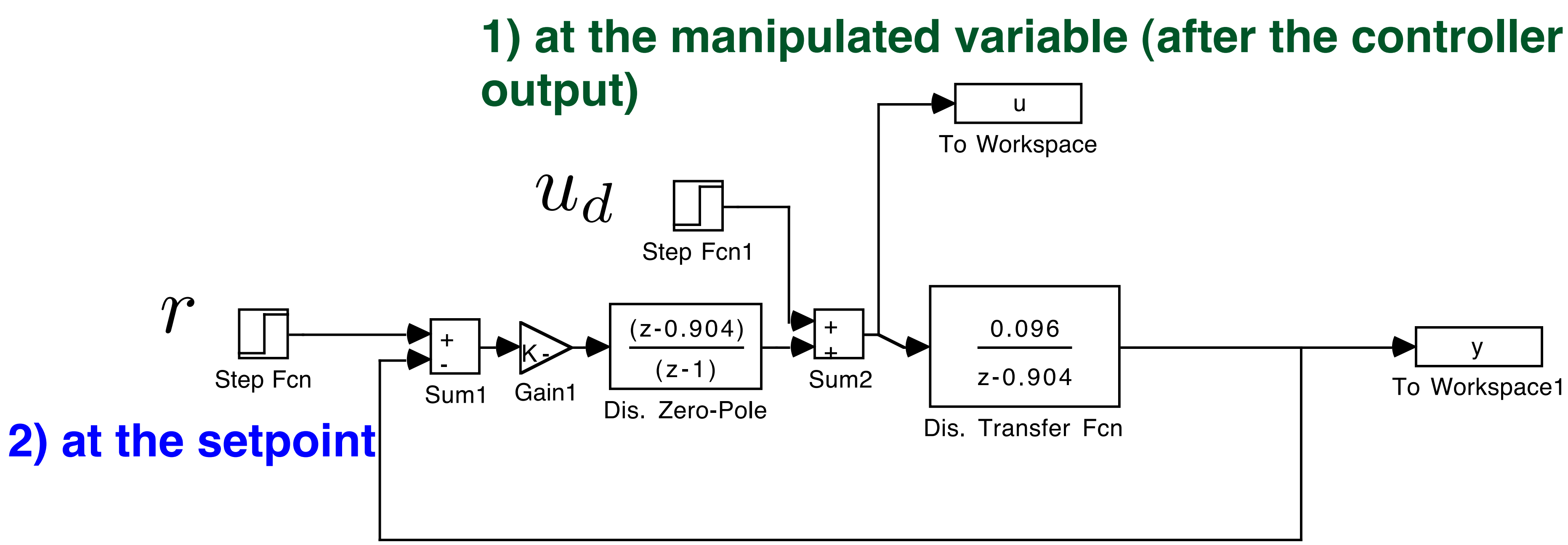
Classical Feedback Control Structure



The responses of the control system are characterized by the closed-loop transfer functions:

$$
\begin{aligned}
y &= \tilde{p}c(1+\tilde{p}c)^{-1}\, r + (1+\tilde{p}c)^{-1}\, d \\
&= \tilde{\eta}\, r + \tilde{\epsilon}\, d \\
u &= c(1+\tilde{p}c)^{-1}\, r - c(1+\tilde{p}c)^{-1}\, d \\
&= \tilde{p}^{-1}\tilde{\eta}\, r - \tilde{p}^{-1}\tilde{\eta}\, d \\
e &= (1+\tilde{p}c)^{-1}\, r - (1+\tilde{p}c)^{-1}\, d \\
&= \tilde{\epsilon}\, r - \tilde{\epsilon}\, d
\end{aligned}
$$

Closed-loop System Identification - Signal Injection Points



We must examine the closed-loop transfer functions between the signal injection points and *u* in order to gain understand how controller tuning impacts the information content on the input signal.

Feedback-Only Closed-Loop Identification

$$\Phi_{e_F} = \left(|p - \tilde{p}|^2 \left(|p^{-1}\eta|^2 \Phi_r + |\epsilon|^2 \Phi_{u_d} \right) + |1 + \tilde{p}c|^2 |\epsilon|^2 \Phi_\nu \right) \frac{|L|^2}{|\tilde{p}_e|^2}$$

The effect of $(1 + \tilde{p}c)$. Bias will be present in closed-loop identification even if u_d, r, and ν are uncorrelated and $\tilde{p}$ and $\tilde{p}_e$ are independently parametrized. For frequencies where Φ_ν predominates, Φ_{e_F} is minimized (i.e., $\Phi_{e_F} \approx 0$) when

$$\tilde{p} = -\frac{1}{c}$$

- often 1/c is not causal, hence this is not fully observed.

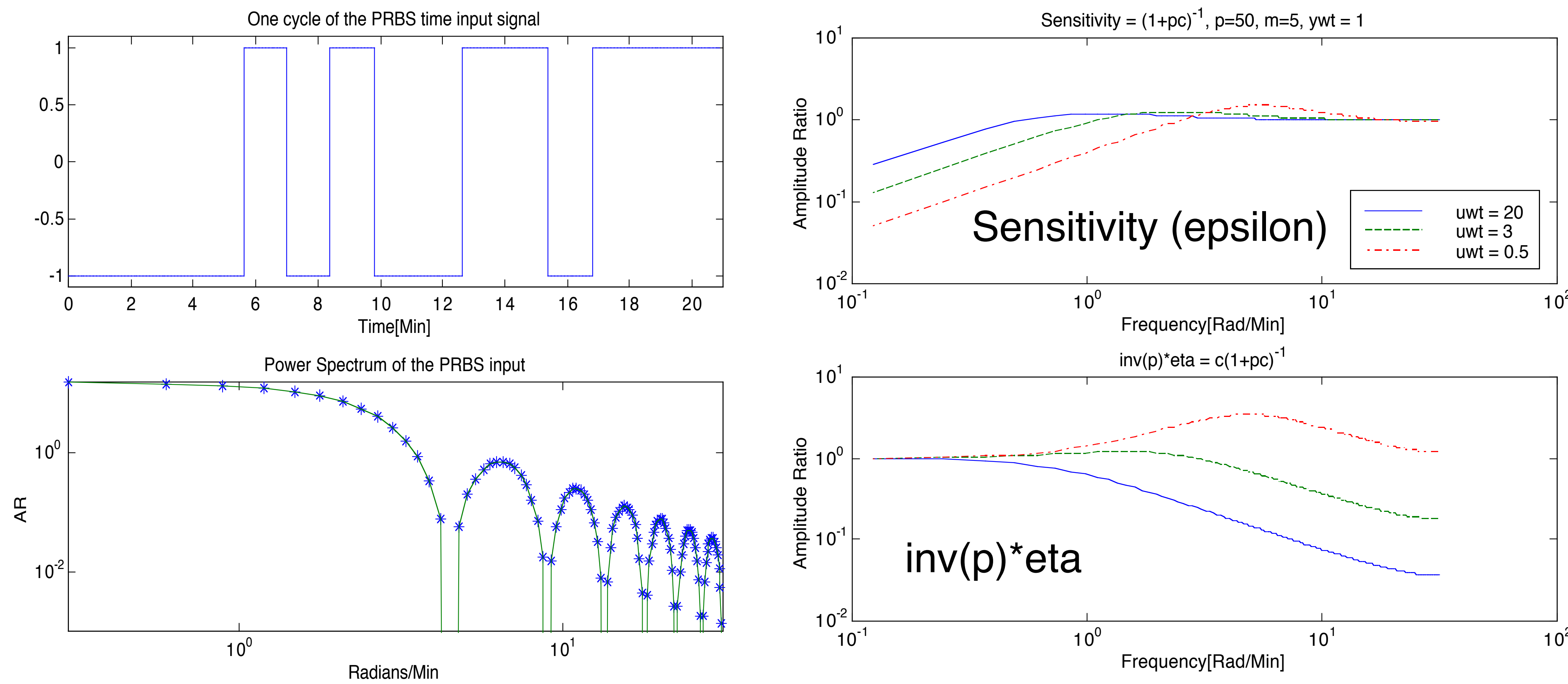
For frequencies where $\Phi_{u_d}/\Phi_\nu \gg 1$ or $\Phi_r/\Phi_\nu \gg 1$ then unbiased estimation of $\tilde{p}$ is possible

$$\tilde{p} = p$$

The closed-loop transfer functions $p^{-1}\eta$ *and* ϵ. These will either attenuate or amplify portions of the external signals u_d and r.

Understanding C-L Signal Injection Pts

$$\Phi_{e_F} = \left(|p-\tilde{p}|^2\left(|p^{-1}\eta|^2\Phi_r + |\epsilon|^2\Phi_{u_d}\right) + |1+\tilde{p}c|^2|\epsilon|^2\Phi_\nu\right)\frac{|L|^2}{|\tilde{p}_e|^2}$$



Variance Considerations - Direct Approach

For large n (model order) and large N (number of data), the asymptotic covariance for the unbiased model estimate is:

$$\mathrm{Cov}\begin{bmatrix} \tilde{p}(e^{j\omega}) \\ \tilde{p}_e(e^{j\omega}) \end{bmatrix} \sim \frac{n}{N}\Phi_\nu(\omega)\begin{bmatrix} \Phi_u(\omega) & \Phi_{ua}(\omega) \\ \Phi_{au}(\omega) & \sigma_a^2 \end{bmatrix}^{-1}$$

$$\begin{aligned} \Phi_u &\equiv \text{Input Power Spectrum} \\ \Phi_\nu &\equiv \text{Disturbance Power Spectrum} \; = |H(e^{i\omega})|^2\sigma_a^2 \\ \Phi_{ua} = \Phi_{au}^* &\equiv \text{Crosspectrum between } u(t) \text{ and } a(t) \end{aligned}$$

One can directly solve for the (1,1) element to obtain

$$\mathrm{Cov}\tilde{p}(e^{j\omega}) \sim \frac{n}{N}\Phi_\nu(\omega)\left(\frac{\sigma_a^2}{\sigma_a^2\Phi_u - |\Phi_{ua}(\omega)|^2}\right)$$

Variance Considerations (Continued)

For the case of u_d and r as external signals, uncorrelated with ν,

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

Variance is still a function of the noise-to-input signal power, except that the input signal power is now influenced by control action.

Comparing the output spectrum for closed-loop operation

$$\Phi_y = |p|^2\Phi_u^{\text{ext}} + |\epsilon|^2\Phi_\nu$$

with that from open-loop operation

$$\Phi_y^{\text{open}} = |p|^2\Phi_u + \Phi_\nu$$

one can conceivably generate closed-loop data that reduces the variance of the output signal without increasing the variance of $\tilde{p}$. This will require, however, a larger (external) input signal magnitude in the closed-loop experiment than that required from an open-loop experiment.

Example 1: No Noise, Unconstrained

Example: First-Order Delay Model. Consider the plant

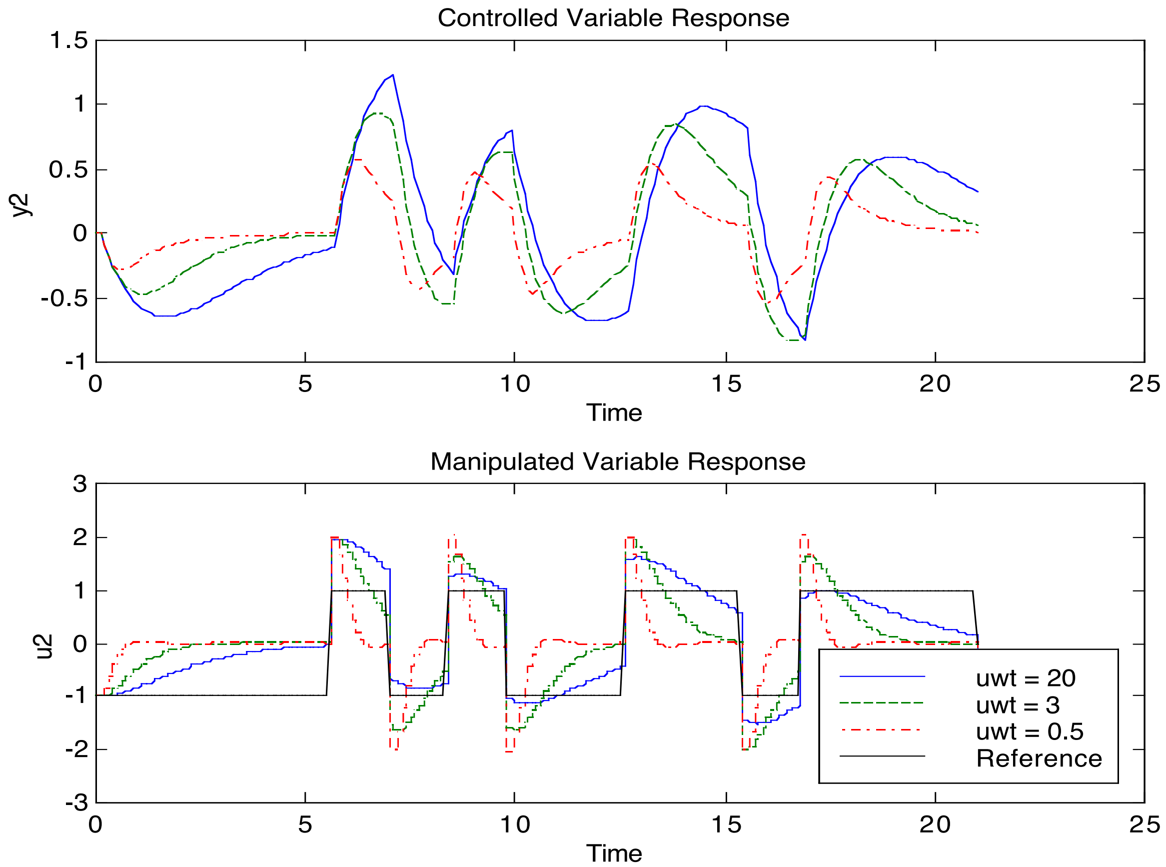
$$p(s) = \frac{e^{-0.1s}}{s+1}$$

sampled at $T = 0.1$. We will consider the following:

- PRBS input design using $\tau_{dom}^{H} = \tau_{dom}^{L} = 1.05$ minutes, $\alpha_s = 2$ and $\beta_s = 3$, leading to switching time $T_{sw} = 1.4$ minutes, 4 shift registers ($n_r = 4$) and a 21 minute total cycle length (NT_{sw}).
- unconstrained MPC control for $p = 50$, $m = 5$, $\Gamma = 1$ and $\Lambda = 20$, 3, and 0.5 at both signal injection points.

Signal Injection, Manipulated Variable Time-Domain Viewpoint

Introduce PRBS changes at the manipulated variable

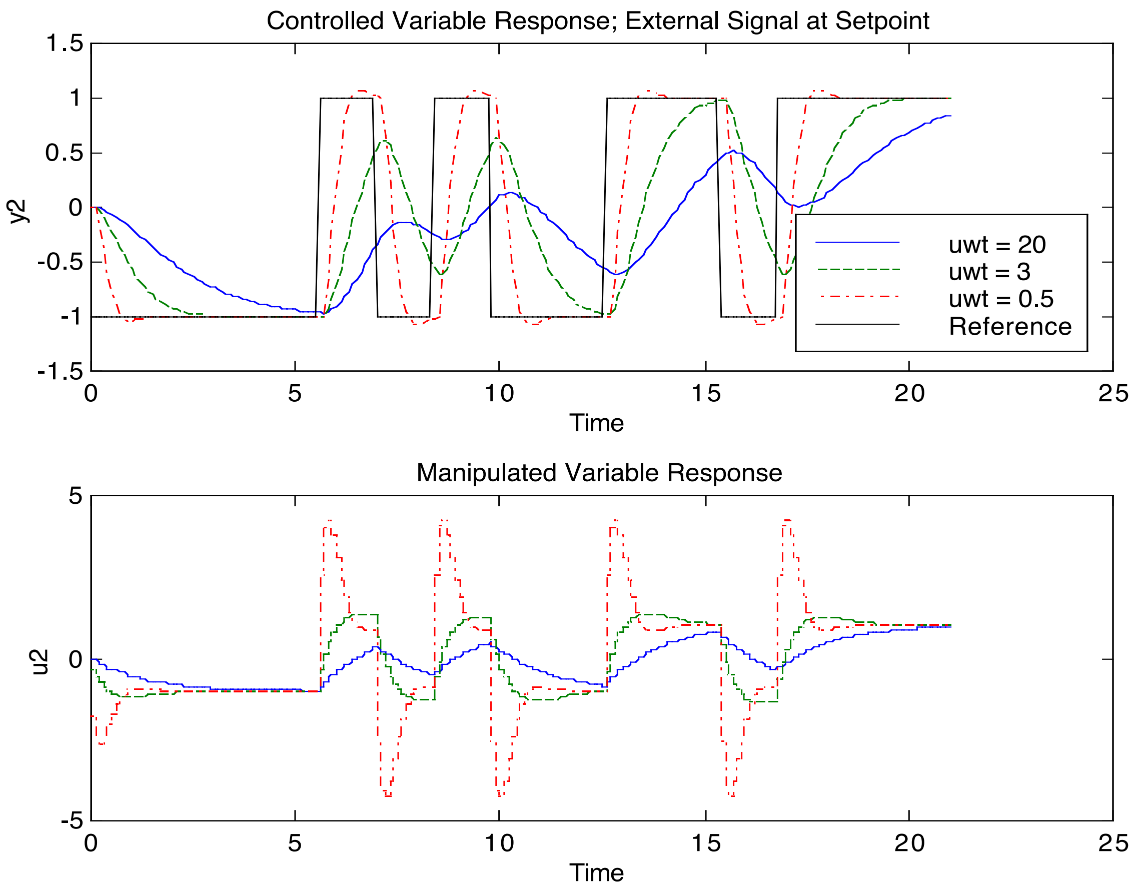


Solid: slow tuning
Dashed: medium (similar to open-loop) tuning
Dashed-dotted: fast tuning

Aggressive tuning attenuates the low frequency portion of the input signal; greater emphasis given to initial-time (high frequency) information at the expense of long-time/steady-state information.

Signal Injection, Setpoint, Time-Domain Viewpoint

Introduce PRBS at the controlled variable setpoint



Solid: slow tuning
Dashed: medium (similar to open-loop) tuning
Dashed-dotted: fast tuning

Aggressive tuning amplifies the high-frequency portion of the input signal; tuning the closed-loop similar to open-loop, however, does not introduce substantial controller bias into the input signal.

Example 2: Unconstrained, with Noise

Consider the same first-order plant as before:

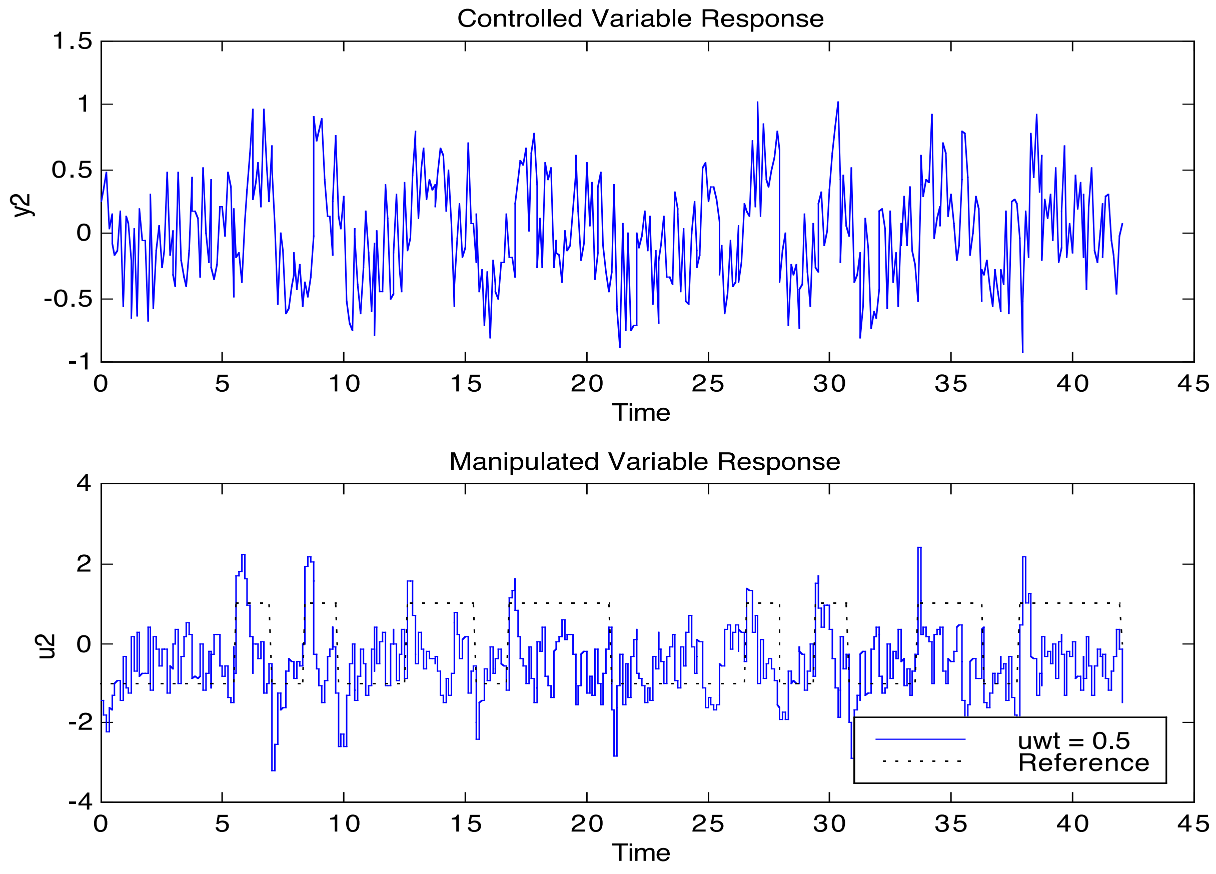
$$y(s) = \frac{e^{-0.1s}}{s+1}u(s) + n(s)$$

sampled at $T = 0.1$. We will consider the following:

- PRBS input design using $\tau_{dom}^{H} = \tau_{dom}^{L} = 1.05$ minutes, $\alpha_s = 2$ and $\beta_s = 3$, leading to switching time $T_{sw} = 1.4$ minutes, 4 shift registers ($n_r = 4$) and a 21 minute total cycle length (NT_{sw}).
- PRBS input magnitude ± 1.5 (at the setpoint) and ± 1.0 (at the manipulated variable). Two cycles of data collected.
- unconstrained MPC control for $p = 50$, $m = 5$, $\Gamma = 1$ and $\Lambda = 0.5$ (for manipulated variable injection) and $\Lambda = 3$ (for setpoint variable injection).
- White measurement noise with identical variance introduced in both cases.

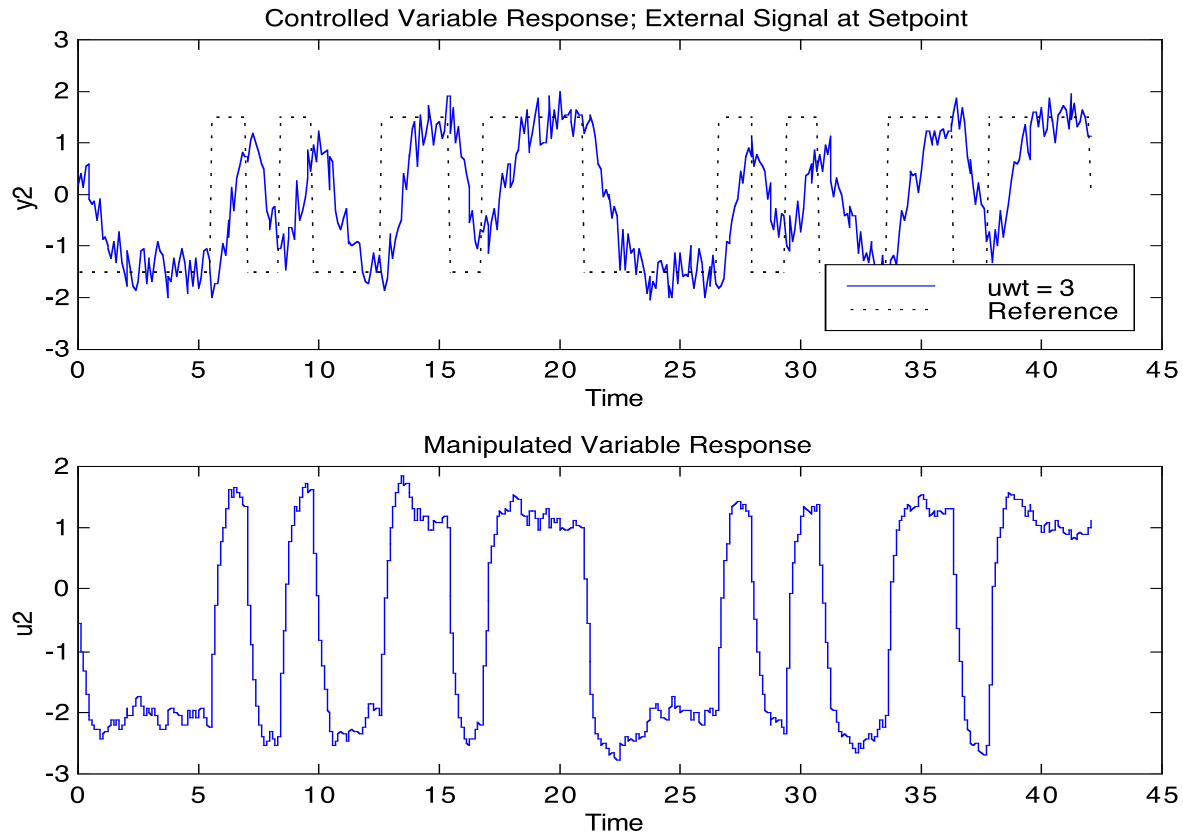
Example 2 Data

Signal Injection at the Manipulated Variable (with an aggressive controller):

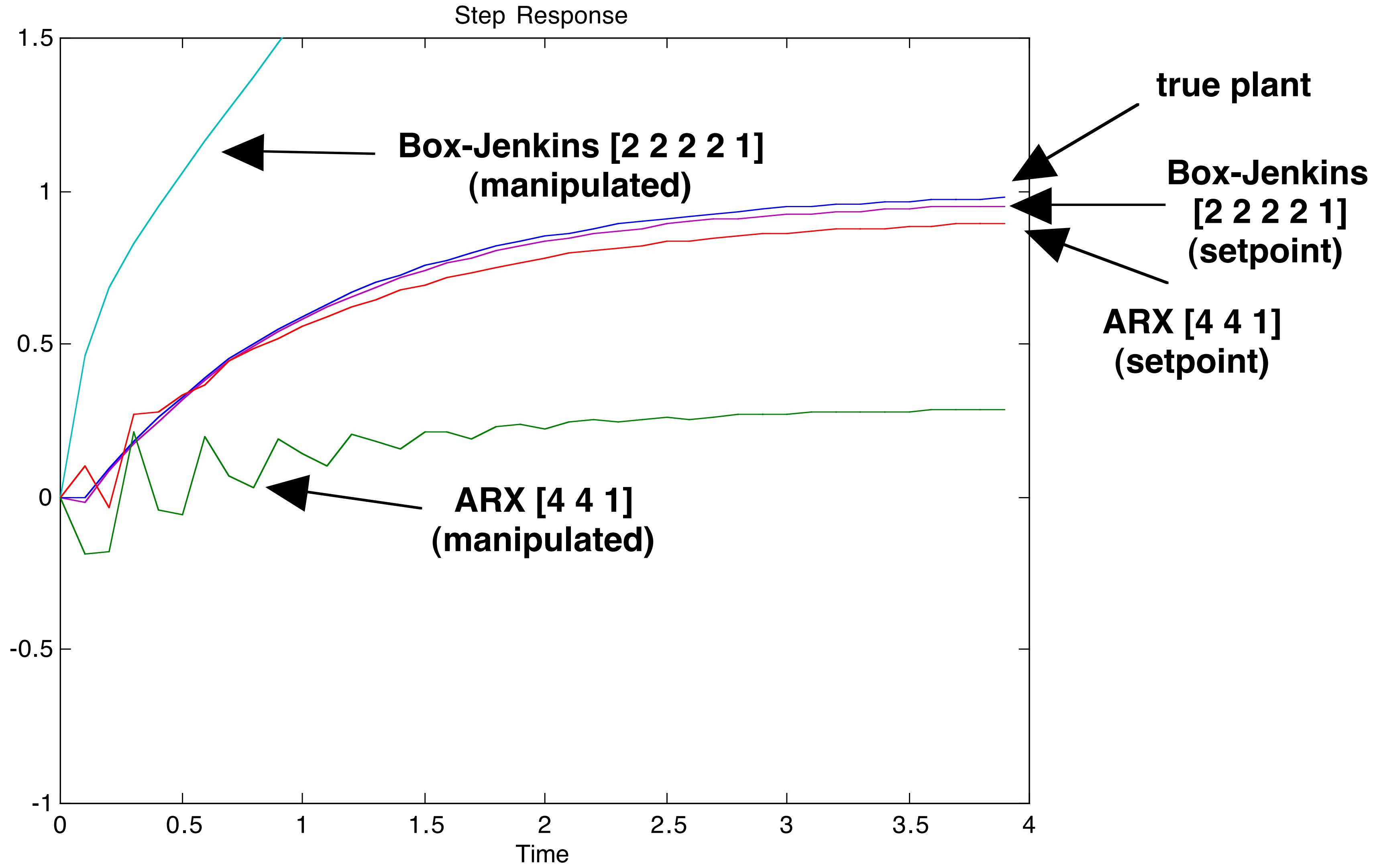


Example 2 Data (Continued)

Signal Injection at the Setpoint (with a moderately tuned controller)



Example 2, Parameter Estimation Results



Model Step Response Comparison

http://aer.ual.es/ITCLI

ITCLI: An Interactive Tool for Closed-Loop Identification

aer.ual.es/ITCLI/

ASU CSEL.ASU.EDU IEEE-TCSIAC IEEE-TCMHCS ASU BB9 BBVA YouTube Amazon Wikipedia

UNIVERSIDAD DE ALMERÍA

Other Modules

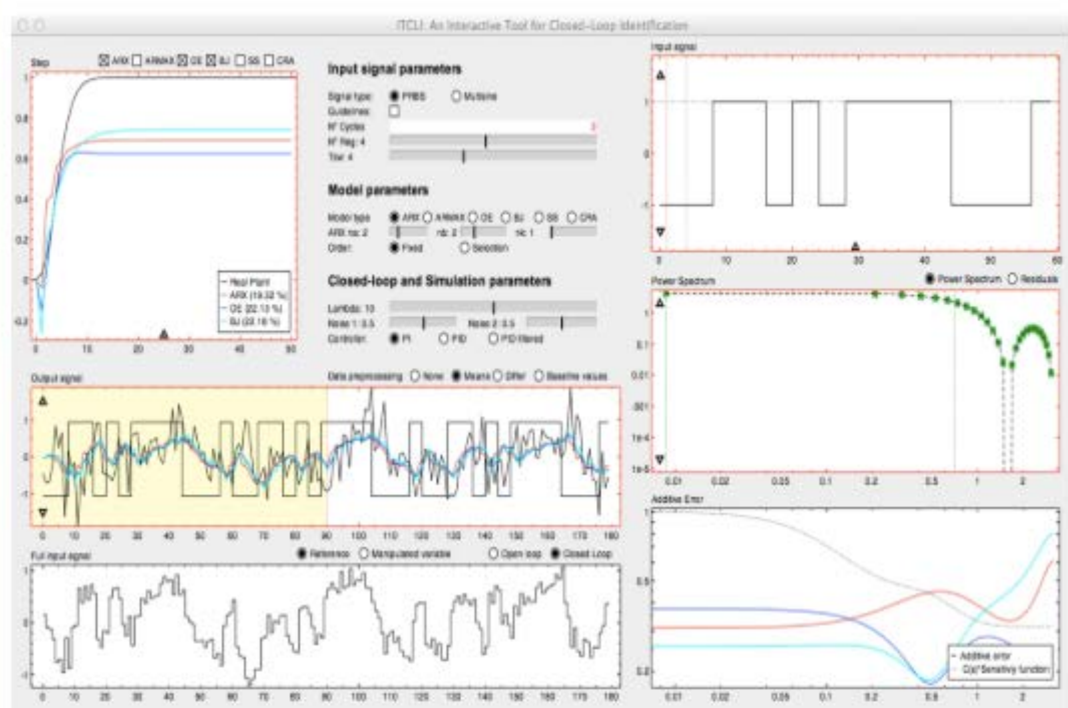
- ILM for PID Control
- Dead-time Control
- Modelling and Identificaiton
- SISO Predictive Control
- MIMO Predictive Control
- Mobile Robotics

Web J.L. Guzmán

ITCLI: An Interactive Tool for Closed-Loop Identification

by J.L. Guzmán, D. Rivera, S. Dormido, and M. Berenguel

The **I**nteractive **T**ool for **C**losed-**L**oop **I**dentification (ITCLI) is 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 mutiple operating environments.



Links

- Calerga
- Google
- CSEL (ASU)
- UNED (Control)
- UAL

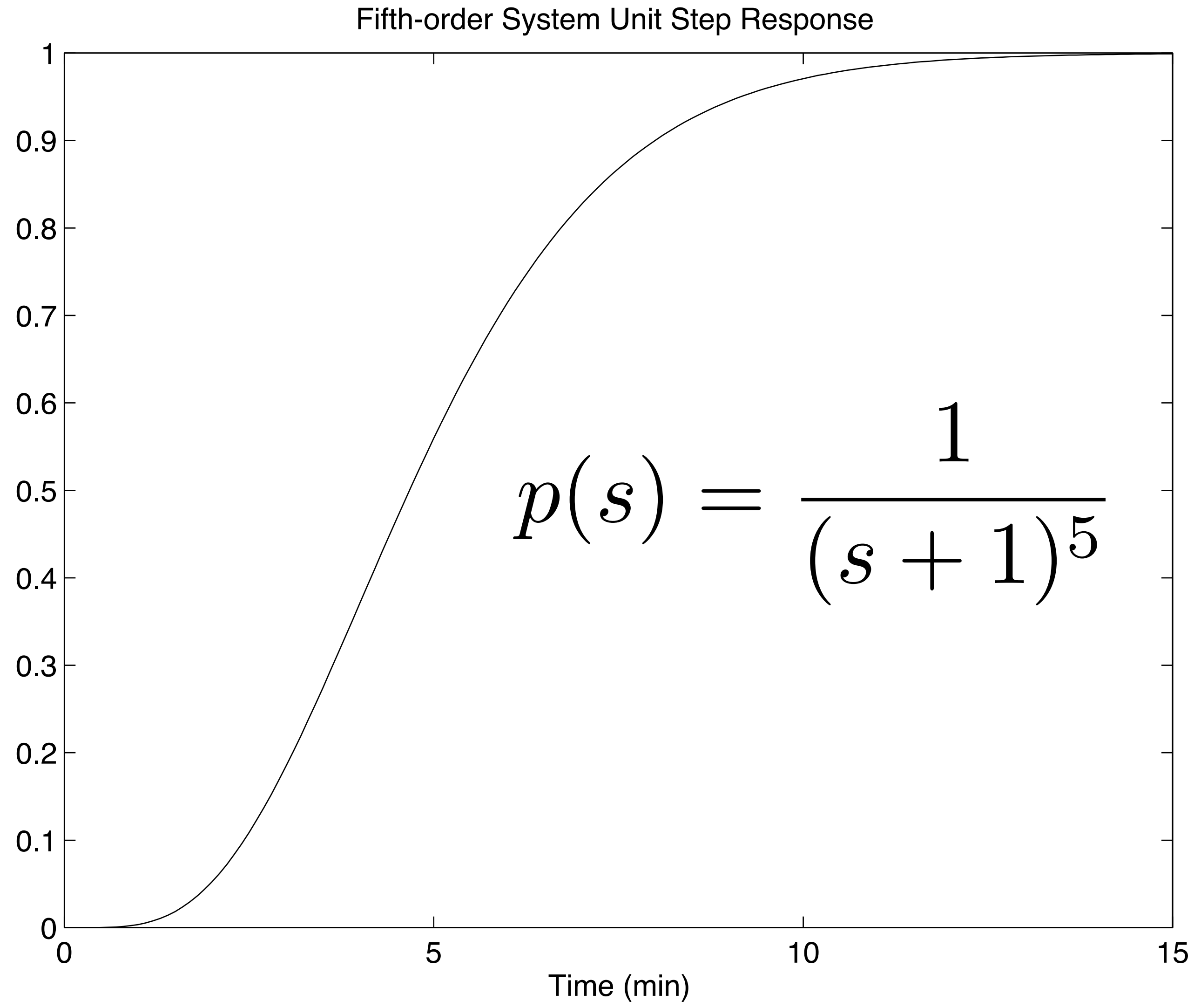
ITSIE Model Simulation Structure

$$y(t) = p(q)\ (u(t) + n_1(t)) + n_2(t)$$

- One output signal, one manipulated input signal, and two unmeasured white noise disturbances (at the input and output, respectively).
- The effect of the input disturbance is a correlated noise signal.
- Currently configured for:
  - the plant as a fifth-order system, and
  - a closed-loop feedback system with PI-PID-PID with filter controllers tuned using the Internal Model Control (IMC) tuning rules and *i-pIDtune*.

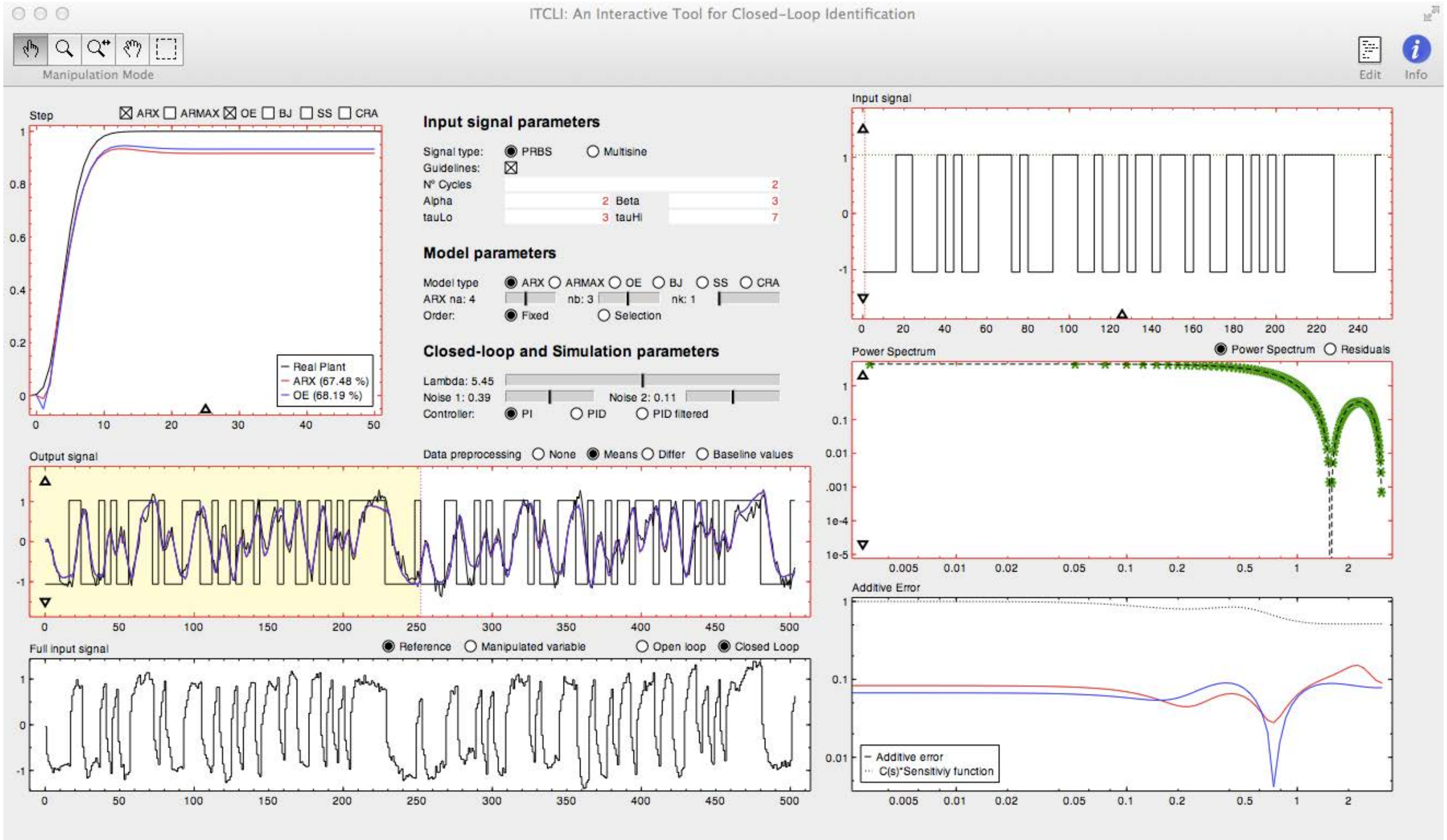
Fifth-order System

$$y(t) = p(q)\ (u(t) + n_1(t)) + n_2(t)$$



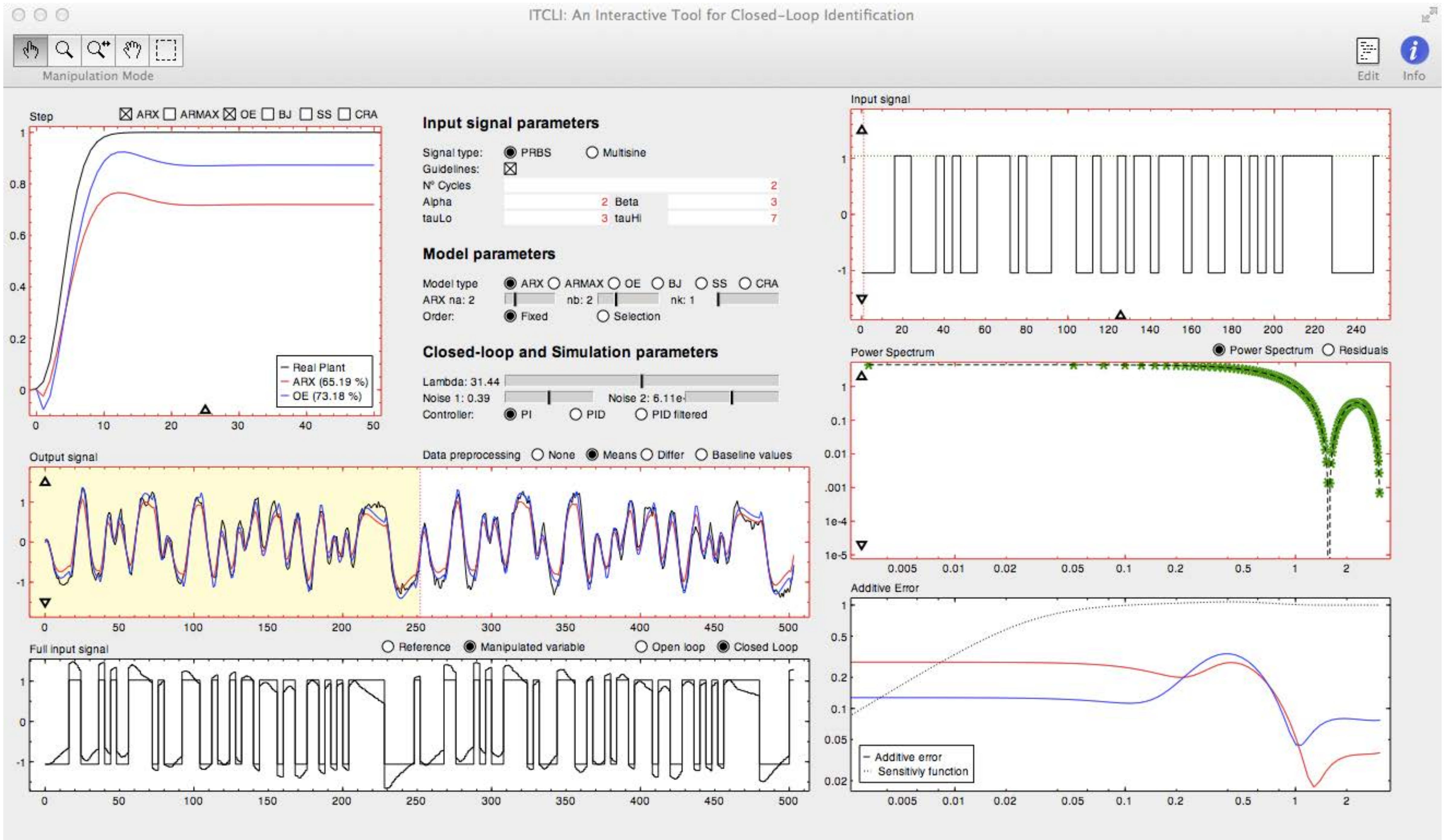
- Unit step response for the fifth-order system evaluated in *ITCLI*.

ITCLI: Case I



- Signal injection at setpoint with sensibly tuned controller.

ITCLI: Case 2

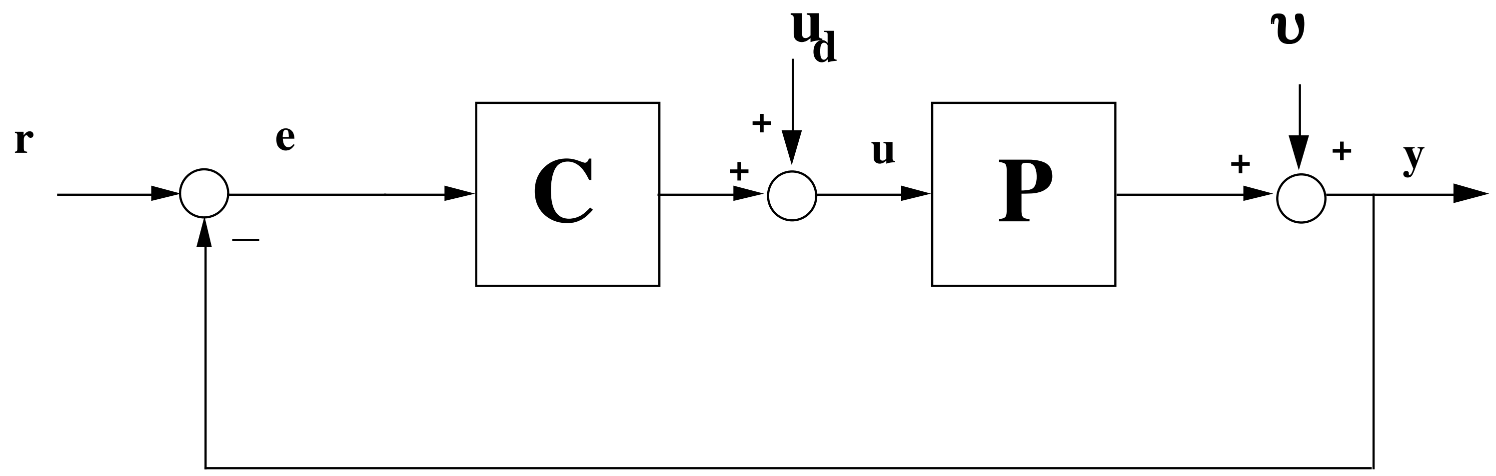


- Signal injection at manipulated variable with very detuned loop.

ITCLI: Case 3

- No external signal; disturbance-driven excitation only.

Closed-Loop Identification: Indirect Approach



For the closed-loop system shown above (let $r = 0$)

$$\begin{aligned} y(t) &= \frac{p(z)}{1+p(z)c(z)} u_d(t) + \frac{1}{1+p(z)c(z)} \nu(t) \\ &= p_{cl}(z) u_d(t) + \nu_{cl}(t) \end{aligned}$$

In the indirect approach, an *open-loop* transfer function estimate for p_{cl} ($\tilde{p}_{cl}$) is estimated from measured u_d and y. *Using knowledge of the transfer function* $c(z)$, an estimate of the plant model $\tilde{p}(z)$ is obtained:

$$\tilde{p}(z) = \frac{\tilde{p}_{cl}(z)}{1 - c(z)\tilde{p}_{cl}(z)}$$

Comments on the Indirect Approach

Paraphrased from Ljung (1997)

- Any method (nonparametric, pem, etc.) can be applied to closed-loop data in this approach.
- Exact knowledge of the compensator model (c(z)) is critical
- Consistent estimation of p(z) is enabled *without* any knowledge of the structure of the noise model
- Covariance properties of the estimate the same as in the direct approach
- Indirect methods based on alternative parametrizations (e.g. coprime, dual Youla) may result in numerical or algebraic benefits, but do not affect the basic statistical properties of the estimate.

Closed-Loop Identification Schemes (Cont.)

- *Two-stage Approach:* Identify the closed-loop system between the external signal and the input (which is in effect an open-loop system); retrive the "noise-free" signal u(t), *without* making use of the controller transfer function!

- *Iterative Refinement Approach:* Iterate between closed-loop identification (from either the direct or indirect approaches) and controller design to arrive at a final model (and control system). Allows for *control-relevant*, closed-loop identification!

Closed-Loop Identification Summary

- an external signal is required in the loop, otherwise strong identifiability conditions are not met.

- controller action introduces correlation between the measurement and affects the frequency content of the input signal, influencing both bias and variance of the estimate

- the purpose feedback is to make the closed-loop system insensitive to open-loop model changes. As a result, closed-loop data typically has less information about the plant than open-loop data (Ljung)

- signal injection at the setpoint (r), under a not-too-aggressive feedback controller, seems sensible from a theoretical standpoint.

Closed-Loop Identification Summary, Continued

- Prediction-error methods applied in a direct fashion with a suitable noise model structure give consistent estimates with optimal accuracy. This is Ljung's recommended approach.

- Be careful with nonparametric methods or other approaches (subspace methods, instrumental variables, PEM with wrong noise models) when using closed-loop data (Ljung).

- Indirect methods offer the opportunity to use both nonparametric or PEM methods without knowledge of the noise model. The controller must be known *a priori*. (Ljung)

- In practice, even a simple controller such as PID may not exactly behave according to its mathematical form. This argues against the use of indirect methods.

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Thank you for your attention!

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