Wiener-Hammerstein benchmark with process noise

M. Schoukens[1], **J.P. Noël**[2]

[1] ELEC Department
Vrije Universiteit Brussel, Brussels, Belgium

[2] Space Structures and Systems Laboratory
Aerospace and Mechanical Engineering Department
University of Liège, Liège, Belgium

1 Introduction

Process noise is already well studied and modeled in the linear time-invariant (LTI) framework. Nonparametric and parametric noise models (Box-Jenkins, ARX, ARMAX) provide good solutions to the LTI process noise problem [1, 2].

Most of the nonlinear modeling approaches only consider additive (colored) noise at the output (see, for instance, the methods listed in [3, 4]), or are restricted to an ARX or ARMAX like noise model (NARX and NARMAX in [5]). Some recent methods consider a more complex noise framework using expectation maximization, particle filter methods, or errors-in-variables approaches [6, 7, 8].

This benchmark presents a Wiener-Hammerstein electronic circuit where the process noise is the dominant noise distortion.

The next sections describe the Wiener-Hammerstein system (Section 2) and describe the data restrictions (Section 3). The test data and the figures of merit that are used in this benchmark are presented in Section 4. Finally, some of the expected challenges during the identification process are listed in Section 5.

2 Wiener-Hammerstein system with process noise

The Wiener-Hammerstein structure is a well known block-oriented system. It contains a static nonlinearity that is sandwiched in between two LTI blocks (Figure 1). The presence of the two LTI blocks results in a problem that is harder to identify. The system is quite similar to the Wiener-Hammerstein system that is studied in an earlier benchmark [9, 10], the main difference is the presence of the process noise.

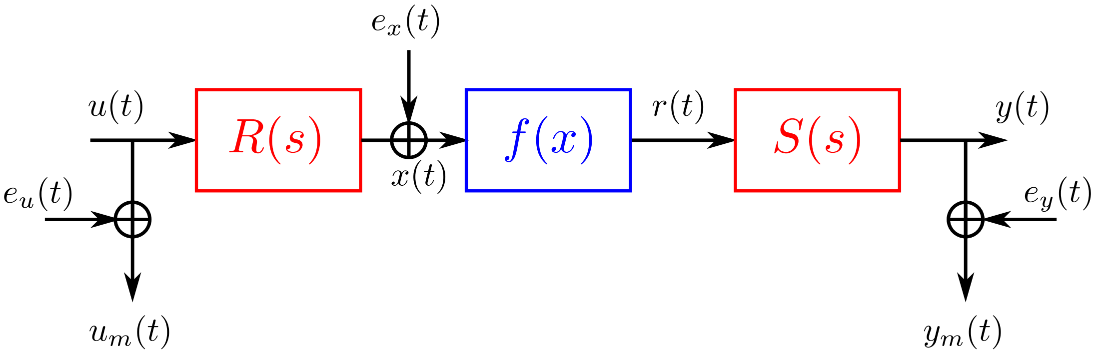

Figure 1: A Wiener-Hammerstein system with process noise. The LTI blocks at the input and the output are depicted by $R(s)$ and $S(s)$ respectively. $f(x)$ denotes the static nonlinearity. The process noise $e_x(t)$ enters the system before the static nonlinearity. Two smaller (neglectable) noise sources $e_u(t)$ and $e_y(t)$ are present in the measurement channels. $u_m(t)$ and $y_m(t)$ are the measured input and output signals.

The first filter $R(s)$ can be described well with a third order lowpass filter. The second LTI subsystem $S(s)$ is designed as an inverse Chebyshev filter with a stopband attenuation of 40 dB and a cutoff frequency of 5 kHz. The second LTI subsystem has a transmission zero within the excited frequency range. This makes the inversion of $S(s)$ difficult.

The static nonlinearity $f(x)$ is realized with a diode-resistor network, this results in a saturation nonlinearity.

The additive process noise $e_x(t)$ is a filtered white Gaussian noise sequence. The filtered noise is generated starting from a discrete-time 3rd order lowpass Butterworth filter followed by a zero-order hold reconstruction and an analog low-pass reconstruction filter with a cut-off frequency of 20 kHz. The noise sources $e_u(t)$ and $e_y(t)$ account for the measurement noise, they can be considered to be white Gaussian noise sources. The dominant noise source is $e_x(t)$, the measurement noise is very small.

3 Data and user guidelines

3.1 Estimation data

The participants are offered the unique opportunity to design the estimation input signals themselves. The measurements are performed at the VUB ELEC department by an experienced user of the measurement setup during 3 different measurement campaigns. The exact dates of these measurement campaigns will be announced to all subscribed participants via e-mail and on the website. All measured input-output data will be offered to the participants to obtain a good model of the system. The possibility for the participants to perform a short measurement campaign at the ELEC department, VUB can be discussed.

- WH Measurement campaign 1: October/November
- WH Measurement campaign 2: January/February
- WH Measurement campaign 3: March

An initial dataset is available on the benchmark meeting website to perform some first analysis and tests on the system. All the data measured by the participants will also be available to all participants through the benchmark meeting website.

A reference signal will be measured during each new measurement campaign to check the reproducibility of the measurements compared to the previous measurements performed on the system.

3.2 Measurement setup

The inputs and the process noise are generated by an arbitrary zero-order hold waveform generator (AWG), the Agilent/HP E1445A, sampling at 78125 Hz. The generated zero-order hold signals are passed through a reconstruction filter (Tektronix Wavetek 432) with a cut-off frequency of 20 kHz. The in- and output signals of the system are measured by the alias protected acquisition channels (Agilent/HP E1430A) sampling at 78125 Hz. The AWG and acquisition cards are synchronized with the AWG clock, and hence the acquisition is phase coherent to the AWG. Leakage errors are hereby easily avoided. Finally, buffers are added between the acquisition cards and the in- and output of the system to avoid that the measurement equipment would distort the measurements.

3.3 User guidelines

The following restrictions apply for the input signals:

- The input signals should be stored in a .mat file,
- The name of the input signal variable is 'input',
- The variable 'input' has the dimension $N \times M$, where N is the number of points in the signals and M is the number of signals that needs to be measured,
- The maximum length of the signal is $N_{max} = 65536$,
- The maximum number of signals in one file is $M_{max} = 100$,
- The amplitude of the signals should be between -4 and 4,
- Note that the sampling frequency is fixed: $f_s = 78125$ Hz.

The measurement file contains a structure 'dataMeas'. This structure has 4 fields:

- r: reference signal, signal loaded into the generator,
- u: measured input signal,
- y: measured output signal,
- fs: the sample frequency.

4 Model test and figure of merit

Two fixed test sets are provided through the benchmark meeting website: a random phase multisine and a sine-sweep signal. Both signals are measured as periodic signals, the datasets contain one steady-state period of the signal. Both measured input signals have an rms value of 0.71 V_{rms}, and they excite the frequencies from DC to 15 kHZ, DC not included. The sine-sweep signal covers the frequency band from DC to 15 kHz at a sweep rate of 4.29 MHz/min.

These test sets function as a target for the obtained model, the model should perform as good as possible on these test datasets. The goal of the benchmark is to estimate a good model on the estimation data. The test data should not be used for any purpose during the estimation. The test sets are measured in the absence of process noise. The noiseless test sets can be used to evaluate the bias on the estimate since wrong noise assumptions can lead to a biased estimate of the system under test [11].

We expect all participants of the benchmark to report the following figure of merit for all test datasets to allow for a fair comparison between different methods:

$$\boldsymbol{e_{RMSt}} = \sqrt{1/N_t \sum_{t=1}^{N_t} (y_{mod}(t) - y_t(t))^2}, \tag{1}$$

where y_{mod} is the modeled output, y_t is the output provided in the test dataset, N_t is the total number of points in y_t.

Also mention whether the modeled output y_{mod} is obtained using **simulation** (only the test input u_t is used to obtain the modeled output $y_{mod}(t) = F(u_t(1), \ldots, u_t(t))$) or **prediction** (both the test input u_t and the past test output y_t are used to obtain the modeled output $y_{mod}(t) = F(u_t(1), \ldots, u_t(t), y_t(1), \ldots, y_t(t-1))$). Provide both figures of merit (simulation and prediction) if the identified model allows for it.

5 Nonlinear system identification challenges

We anticipate the Wiener-Hammerstein benchmark to be associated with 3 major nonlinear system identification challenges:

- the process noise that is present in the system,
- the static nonlinearity which is not directly accessible from neither the measured input or output,
- the output dynamics are difficult to invert due to the presence of a transmission zero.

References

[1] R. Pintelon and J. Schoukens. *System Identification: A Frequency Domain Approach*. Wiley-IEEE Press, Hoboken, New Jersey, 2nd edition, 2012.

[2] L. Ljung. *System Identification: Theory for the User (second edition)*. Prentice Hall, Upper Saddle River, New Jersey, 1999.

[3] F. Giri and E.W. Bai, editors. *Block-oriented Nonlinear System Identification*, volume 404 of *Lecture Notes in Control and Information Sciences*. Springer, Berlin Heidelberg, 2010.

[4] J. Paduart, L. Lauwers, J. Swevers, K. Smolders, J. Schoukens, and R. Pintelon. Identification of nonlinear systems using polynomial nonlinear state space models. *Automatica*, 46(4):647–656, 2010.

[5] S.A. Billings. *Nonlinear System Identification: NARMAX Methods in the Time, Frequency, and Spatio-Temporal Domains*. John Wiley & Sons, Ltd., West Sussex, United Kingdom, 2013.

[6] T.B. Schön, A. Wills, and B. Ninness. System identification of nonlinear state-space models. *Automatica*, 47(1):39–49, 2011.

[7] F. Lindsten, T.B. Schön, and M.I. Jordan. Bayesian semiparametric Wiener system identification. *Automatica*, 49(7):2053 – 2063, 2013.

[8] B. Wahlberg, J. Welsh, and L. Ljung. Identification of Wiener systems with process noise is a nonlinear errors-in-variables problem. In *53rd IEEE Conference on Decision and Control (CDC)*, pages 3328–3333, Dec. 2014.

[9] J. Schoukens, J.A.K. Suykens, and L. Ljung. Wiener-Hammerstein benchmark. In *15th IFAC Symposium on System Identification (SYSID)*, Saint-Malo, France, July 2009.

[10] G. Vandersteen. *Identification of linear and nonlinear systems in an errors-in-variables least squares and total least squares framework*. PhD thesis, Vrije Universiteit Brussel, 1997.

[11] A. Hagenblad, L. Ljung, and A. Wills. Maximum likelihood identification of Wiener models. *Automatica*, 44(11):2697–2705, 2008.