Wiener-Hammerstein Benchmark

J. Schoukens [a]**, J. Suykens** [b]**, L. Ljung** [c]

(a) Vrije Universiteit Brussel, Department ELEC, Pleinlaan 2, B1050 Brussels, Belgium
(b) KULeuven, ESAT, SCD, Kasteelpark Arenberg 10, B-3001 Heverlee, Belgium
(c)Linkoping University, Automatic Control, SE-581 83 Linköping, Sweden
email: johan.schoukens@vub.ac.be

Abstract - This paper describes a benchmark for nonlinear system identification. A Wiener-Hammerstein system is selected as test object. In such a structure there is no direct access to the static nonlinearity starting from the measured input/output, because it is sandwiched between two unknown dynamic systems. The signal-to-noise ratio of the measurements is quite high, which puts the focus of the benchmark on the ability to identify the nonlinear behaviour, and not so much on the noise rejection properties. The benchmark is not intended as a competition, but as a tool to compare the possibilities of different methods to deal with this specific nonlinear structure.

Keywords: Benchmark examples, nonlinear systems, system identification

1. Introduction

The aim of this benchmark is to compare different black box identification methods to model nonlinear systems. The aim of the benchmark is not to setup a competition. It is well known that it is always possible to create experimental conditions that favourite a given modelling approach. The goal is to get a better understanding about the capabilities of different modelling and identification methods. From this point of view it is not only interesting to see how well a method is doing, also from a failure to model the data can be learned a lot!

We deliberately did not include an ‘extrapolation’ part where the model is used outside the range where it was estimated (in amplitude or frequency range). It is always possible to construct a test system that behaves in an undesirable way for a given model, while it perfectly fits the extrapolation for another model class.

A real-life data set is made available. A description of the nonlinear system, the measurement setup, and the data is given. Finally we describe how the results should be reported.

This benchmark continues a series of tests on the silverbox-system which is a system with a static nonlinear feedback. That study was presented at the 6th IFAC symposium NOLCOS 2004 - Stuttgart: Symposium on Nonlinear Control Systems, in the session “Identification of nonlinear systems: The silverbox case study”.

2. Nonlinear System

To emphasize the non-competitive aspects, we give a much more detailed description of the test-system than what is needed for a black-box modelling approach. The reason for that is to make clear to all participants that there are no hidden pitfalls. The reader should be aware that the actual system does not perfectly match this idealized description, due to interactions between the different building blocks and the use of non ideal components. For example, the behaviour of the ‘static nonlinearity’ will be affected by the interaction with the output impedance of the first linear system, and the input impedance of the second linear system.

The system to be modelled is an electronic nonlinear system with a Wiener-Hammerstein structure that was built by Gerd Vandersteen (Vandersteen, 1997). The general structure is shown in Fig. 1.

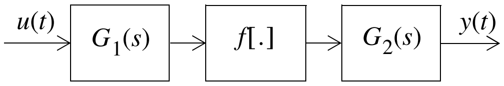

Fig. 1: Wiener-Hammerstein system consisting of the cascade of a linear dynamic block $G_1(s)$, a static non-linear block $f[.]$ and a linear dynamic block $G_2(s)$

The first filter $G_1(s)$ is designed as a third order Chebyshev filter (pass-band ripple of 0.5 dB and cut off frequency of 4.4 kHz).

The second filter is designed as a third order inverse Chebyshev filter (stop-band attenuation of 40 dB starting at 5 kHz). This system has a transmission zero in the frequency band of interest. This can complicate the identification significantly, because the inversion of such a characteristic is difficult.

The static nonlinearity is built using a diode circuit(Fig. 2).

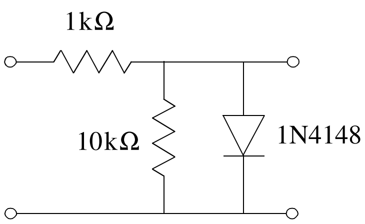

Fig. 2: Circuit used to built the static nonlinear system.

An impression of the overall characteristic is given in Fig. 3

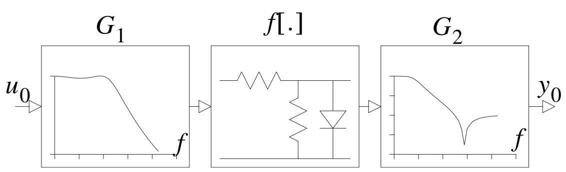

Fig. 3: The Wiener-Hammerstein system.

3. EXPERIMENT

The Wiener-Hammerstein system was excited with a filtered Gaussian excitation signal (cut-off frequency 10 kHz).

The input is generated using an HPE1434A arbitrary waveform generator. This is a zero-order-hold (ZOH) generator, followed by an analog low-pass filter to filter the high frequency components of the ZOH-reconstruction, so that the resulting signal is a band-limited signal.

The input and output were measured with a HPE1433A data acquisition card using a sample frequency of 51200 Hz. An internal anti-alias filter is present in this card.

The measured signals are shown in Fig. 4. An impres-

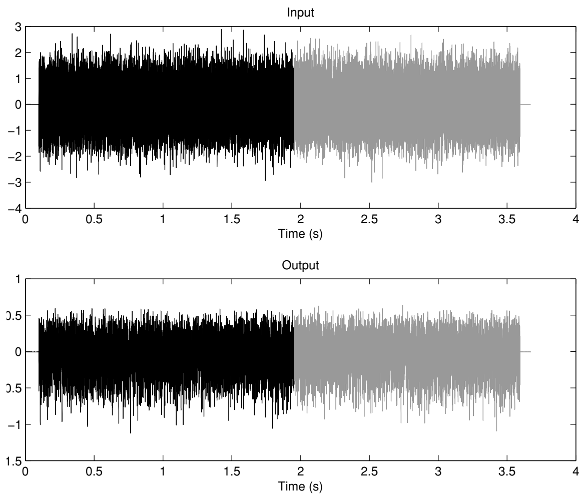

Fig. 4: Measured input and output signal. Black part: estimation data (user available data to built the model); gray part: test data: to be used only for bench marking).

sion of the disturbing noise levels can be found by zooming in on the non-excited parts. It turns out that the disturbing noise levels (measurement noise) are very low, and about 70 dB below the signal levels (see also Fig. 6).

The amplitude distribution of the input and output signal (leaving out the zero-parts) is given in Fig. 5. From

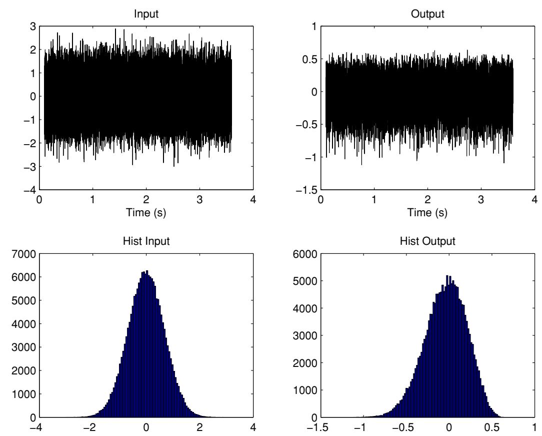

Fig. 5: Histogram of the measured input and output.

this figure it can be seen that the input is Gaussian distributed, while the output is clearly skew.

The discrete Fourier transform (DFT, with hanning window) of the input and output is shown in Fig. 6.

Also the FRF (frequency response function) of the nonparametric best linear approximation that is obtained from these data is shown. From the input spec-

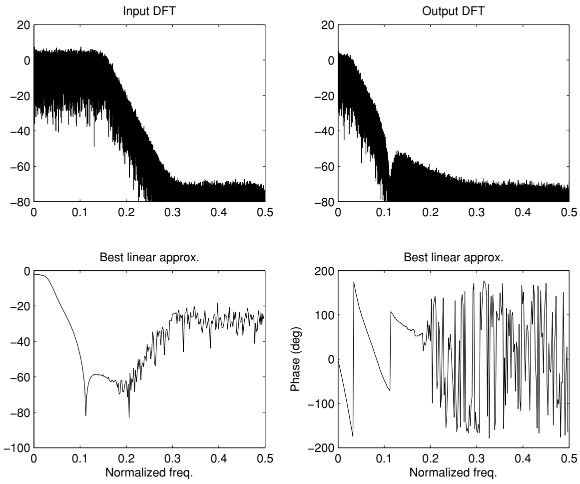

Fig. 6: Top: the amplitude of the Discrete Fourier transform of the measured input and output. Bottom: The FRF of the best linear approximation. Left: amplitude; right: phase.

trum, it can be seen that the input signal is low-pass filtered. In the FRF, the transmission zero of the second filter is clearly visible.

4. The Benchmark

We split the data record in two parts: the *estimation data*, and the *test data*. The estimation data are the only data to be used to estimate and validate the model, while the test data will be used to bench mark the quality of the estimated model. The test data should not be used for any purpose during the tuning of the model (parameter estimation, model selection, early stopping, ...). Algorithms that need two or more separate data sets during the identification step should split the estimation data.

In this benchmark the estimation data are the first part of the measured input and output data $u(t), y(t)$ ($t = 1, 2, \ldots, 100000$) plotted in black in Fig. 4, the test data are given by the remaining part ($t = 100001, \ldots, 188000$) that is plotted in gray in Fig. 4.

The goal of the benchmark is to identify a nonlinear model (discrete or continuous time) using the estimation data.

Next this model is used to simulate the output $y_{sim}(t)$ of the system on the validation set. Simulation is defined as calculating the output, using only the measured input data. No past values of the measured output should be used (= prediction error), see Ljung (1999) for more details.

Besides a description of the identification method, and the model, the following results on the test data set should be given in order to allow a comparison of the results:

- A plot with the modelled output and the simulation error $e_{sim}(t)$ in the time domain (linear plot) and in the frequency domain (semi-logarithmic plot, or plot in dB).

- The mean value of the simulation error (time domain):

$$\mu_t = \frac{1}{87000} \sum_{t = 101001}^{188000} e_{sim}(t) . \tag{1}$$

In (1), the sum is started at $t = 101000$ instead of $t = 100000$ to eliminate the influence of transient errors at the beginning of the simulation.

- The standard deviation of the error (time domain)

$$s_t = \sqrt{\frac{1}{87000} \sum_{t = 101001}^{188000} (e_{sim}(t) - \mu_v)^2} \tag{2}$$

- the root mean square (RMS) value of the error (time domain)

$$e_{RMSt} = \sqrt{\frac{1}{87000} \sum_{t = 101001}^{188000} e_{sim}(t)^2} \tag{3}$$

Give also the same results for the estimation data, calculating the sums over $t \in [1001, 100000]$, for example:

$$e_{RMSe} = \sqrt{\frac{1}{99000} \sum_{t = 1001}^{100000} e_{sim}(t)^2} . \tag{4}$$

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