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Three Benchmarks Addressing Open Challenges in Nonlinear System Identification ⋆

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Abstract: Nonlinear system identification is a fast evolving field of research with contributions from different communities. It is not always straightforward to compare different models and identification approaches. Therefore it is of high importance to offer well chosen benchmarks to the nonlinear system identification community. The interaction generated by such a benchmark can push the state of the art in nonlinear system identification forward.
This paper discusses some challenges that are present nowadays in the nonlinear system identification community. Three benchmarks are presented, a hysteretic benchmark, a Wiener-Hammerstein benchmark, and a cascaded tanks benchmark, each addressing one or more of these challenges.

Keywords: Nonlinear System Identification, Benchmark Systems, Hysteresis, Wiener-Hammerstein, Process Noise, Cascaded Tanks, Short Data Record

1. INTRODUCTION

Nonlinear system identification is a fast evolving field of research with contributions from different communities, such as the mechanical engineering, systems and control and machine learning communities. Many identification methods and algorithms have been developed over the last years, for a wide variety of model structures. Block-oriented structures (Giri and Bai, 2010; Schoukens et al., 2015), nonlinear state-space representations (Paduart et al., 2010; Schön et al., 2011), NARX and NARMAX models (Billings, 2013) and piecewise linear models (Mattsson et al., 2016) are some examples of different nonlinear system representations.

It is not always straightforward to compare different models and identification approaches due to the difference between the model structures, the many possible trade-offs (e.g. model complexity, model flexibility, computational load, accuracy and interpretability of the model), the differences between the assumptions that are made and the different backgrounds of the communities involved in nonlinear system identification. Carefully selected and well described benchmarks are of great importance for the validation and comparison of newly developed nonlinear identification algorithms. A benchmark using a real-life system can also be used to validate the robustness of an identification algorithm with respect to non-idealities that are typically encountered in a practical measurement setup and a real-life system (e.g. system does not belong exactly to the model set, slightly violated noise assumptions, non-idealities in the measurements). A well constructed benchmark allows a researcher to more easily understand the strengths and weaknesses of each identification algorithm and the differences between the proposed approaches. Moreover, a well chosen benchmark can increase the interaction and collaboration between the different identification communities by working side by side on the same identification challenge.

Only a limited number nonlinear system identification benchmark datasets are publicly available (see for instance (Wigren and Schoukens, 2013; Schoukens et al., 2009)). Some more interesting setups are collected and described in (Kroll and Schulte, 2014), where the focus lies, depending on the considered benchmark, on identification and/or control.

We believe that it is of crucial importance not to see a benchmark in this setting as a competition, but rather as an opportunity to illustrate the capabilities and limitations of an identification method. Such an interaction can drive the nonlinear system identification field forward, by identifying some common shortcomings in the state of the art, or by combining two or more state-of-the-art approaches to obtain an even more advanced identification algorithm.

This paper introduces three new nonlinear system identification benchmarks to a wide audience. It also serves as an introduction paper on the IFAC 2017 open invited track on Nonlinear System Identification Benchmarks. A discussion on the type of identification approaches that can be applied on the presented benchmarks and datasets is beyond

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the scope of this paper. The remainder of this paper first discusses some challenges that are present nowadays in the nonlinear system identification community (Section 2). Three benchmarks, a hysteretic benchmark with a dynamic nonlinearity (Noël and Schoukens, 2016), a Wiener-Hammerstein benchmark with process noise (Schoukens and Noël, 2016), and a cascaded tanks benchmark combining soft and hard nonlinearities (Schoukens et al., 2016), addressing one or more of these challenges are introduced next in Sections 3, 4 and 5.

2. SOME CHALLENGES IN NONLINEAR SYSTEM IDENTIFICATION

There are quite some challenges to tackle in the nonlinear system identification community. This paper highlights three of them: dynamic nonlinearities, process noise and short data records.

This paper does not offer any solution to these benchmarks, many possible approaches can be applied, and obtain satisfying results. The benchmarks presented in this paper allows us to better understand the advantages and drawbacks of new state-of-the-art nonlinear identification approaches.

2.1 Dynamic Nonlinearities

Dynamic nonlinearities such as hysteretic nonlinearities appear in many engineering disciplines ranging from solid mechanics (Morrison et al., 2001), electromagnetism (Bertotti, 1985) and aerodynamics (Mueller, 1985). A hysteresis nonlinearity is governed by internal states, not accessible from the measured input or output. The (black-box) identification of hysteretic nonlinearities is studied recently using, for example, augmented Hammerstein structures (Wang et al., 2012; Yong et al., 2015), NARX (Worden and Barthorpe, 2012), Neural Network based structures (Xie et al., 2013) and nonlinear state-space structures (Noël et al., 2016).

The challenge of identifying a dynamic system with a hysteretic nonlinearity in feedback is addressed by the benchmark presented in Section 3.

2.2 Process Noise

Many nonlinear identification methods are limited to an additive (colored) noise source located at the output of the system, or are restricted to a NARX or NARMAX type of noise model. Such a noise framework is a simplified representation of reality which can lead to biased estimates, e.g. due to process noise passing through a nonlinear subsystem (Hagenblad et al., 2008). A more realistic noise framework can be obtained by introducing multiple noise sources, or by placing the noise source at a different location in the considered system structure. Multiple noise sources are considered in a limited number of contributions: e.g. (Hagenblad et al., 2008; Wills et al., 2013; Lindsten et al., 2013; Wahlberg et al., 2014). This more realistic noise framework comes often at the cost of a more complex identification algorithm.

The Wiener-Hammerstein benchmark with process noise presented in Section 4 challenges the research community to deal with a dominant process noise source during the identification of a Wiener-Hammerstein system.

2.3 Short Data Records

Classical (black-box) nonlinear system identification methods often require a relatively high amount of data to obtain a high quality model which demonstrates good generalization capabilities on a validation data record. The number of data points needed can be reduced by introducing prior knowledge, or physical insight into the model structure (e.g. through regularization (Risuleo et al., 2015) or using a structured (grey-box) models).

The challenge of identifying a nonlinear system using short data records is addressed by the cascaded tanks benchmark combining soft and hard nonlinearities in Section 5.

3. HYSTERETIC BENCHMARK WITH A DYNAMIC NONLINEARITY

A more in-depth description of the hysteretic benchmark with a dynamic nonlinearity is provided in (Noël and Schoukens, 2016).

3.1 System

The Bouc-Wen model (Bouc, 1967; Wen, 1976) has been intensively used to model hysteretic effects in mechanical engineering, especially in the case of random vibrations. An extensive literature review about Bouc-Wen modeling can be found in (Ismail et al., 2009; Ikhouane and Rodellar, 2007).

The vibrations of a single-degree-of-freedom Bouc-Wen system, i.e. a Bouc-Wen oscillator with a single mass, are given by (Wen, 1976)

$$m_L\,\ddot{y}(t) + r(y, \dot{y}) + z(y, \dot{y}) = u(t), \quad (1)$$

where m_L is the mass constant, y the displacement, u the external force, and where an over-dot indicates a derivative with respect to the time t. The restoring force in the system is composed of a static nonlinear term $r(y, \dot{y})$, which only depends on the instantaneous values of the displacement $y(t)$ and velocity $\dot{y}(t)$, and of a dynamic nonlinear term $z(y, \dot{y})$, which represents the hysteretic memory of the system. Here we assume that the static restoring force contribution is linear:

$$r(y, \dot{y}) = k_L\,y + c_L\,\dot{y}, \quad (2)$$

where k_L and c_L are the linear stiffness and viscous damping coefficients, respectively. The hysteretic force $z(y, \dot{y})$ obeys the first-order differential equation

$$\dot{z}(y, \dot{y}) = \alpha\,\dot{y} - \beta\left(\gamma\;|\dot{y}|\,|z|^{\nu-1}\,z + \delta\,\dot{y}\,|z|^{\nu}\right), \quad (3)$$

where the five Bouc-Wen parameters α, β, γ, δ and ν are used to tune the shape and the smoothness of the system hysteresis loop. Table 1 lists the values of the physical parameters selected in this study. The system parameters m_L, c_L and k_L given in Table 1 result in a linear modal natural frequency $\omega_0 = 35.59$Hz and a damping ratio $\zeta = 1.12\%$. The Bouc-Wen parameter values in Table 1 were selected to lead to appreciable nonlinear manifestations under reasonable forcing levels. More specifically, in the two test data sets described below, the natural frequency