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IFAC PapersOnLine 50-1 (2017) 470–475

Automatic Modeling with Local Model Networks for Benchmark Processes

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Abstract: In this paper an automated model generation framework is used to identify three nonlinear dynamic benchmark processes. The nonlinearity is approximated using tree-based local model networks (LMN) with external dynamics, which are represented by three different approaches: NARX, NFIR and NOBF. The automated method assumes no prior knowledge about the process, and aims to be a ready-to-use tool for system identification. Results are given for the different approaches and benchmark processes. The importance of the choice of training data for a good generalizing model performance is discussed.

Keywords: Local Model Network, LMN, HILOMOT, LOLIMOT, System Identification, Benchmark Process, Bouc-Wen, Wiener-Hammerstein, Cascaded Tanks, Nonlinear Dynamic Systems, NARX, NFIR, NOBF

1. INTRODUCTION

Nonlinear system identification of dynamic systems is still a challenging research area. This paper is concerned with the application of an automated model generation framework (based on local model networks) to three proposed benchmark systems (Bouc-Wen, Wiener-Hammerstein, Cascaded Tanks). The main goal here is to obtain as much information about the system from given data as possible, without the use of any process specific prior knowledge. It will be interesting to see how this approach performs compared to algorithms incorporating specific knowledge used for these benchmark processes by other authors. The following results will be provided:

- A thorough description of the different levels of automatic modeling for dynamic systems.
- The application of tree based local model networks (LMN, here e.g. HILOMOT) for the benchmark problems using three different dynamic representations (NARX, NFIR and NOBF [1]) and a report of the respective figures of merit.
- An analysis of different input signals and the effect of the black-box model performance is provided for the Bouc-Wen system.

First, in Sec. 2, the concept of an automated model generation framework is presented. The general aspects such an approach has to cover are: Selection of training data (design of experiments), determination of relevant inputs, choice of the (dynamic) structure and the identification of the (hyper-) parameters of the model. A brief description is given how these aspects are addressed by the methods used in this paper. Section 3 presents the results for the automated identification of the three benchmark systems. Finally, in Sec. 4, a conclusion is given.

[1] The prefixed 'N' indicates the usage in combination with a nonlinear approximator for all three dynamic structures.

2. A FRAMEWORK FOR AUTOMATIC MODEL GENERATION

2.1 The Vision of Automatic Modeling

Nonlinear system identification of discrete time dynamic systems focuses on identifying a relationship

$$y(k) = f(u(k), u(k-1), \ldots, u(k-n), \\ y(k-1), \ldots, y(k-n)) \quad (1)$$

from a given dataset $D = \{u(k), y(k)\}_1^N$, where $f(\cdot)$ is some nonlinear mapping, $u(k)$ is the input of the system and $y(k)$ is the output of the system at the discrete time step k. In the subsequent sections we will use the term *automatic modeling* to describe the nested optimization process of model building depicted in Fig. 1. For complete automatic modeling these several levels have to be optimized subsequently by the applied method.

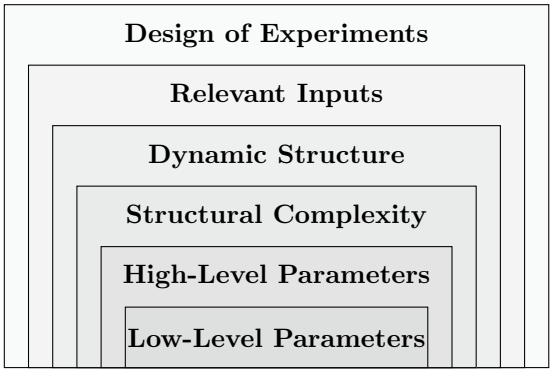

Fig. 1. Hierarchical structure of the nested optimization problems to be solved in automatic modeling.

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2017.08.089

Design of Experiments The design of experiments (DoE) is the first step, when identifying dynamic systems. In the current contribution we restrict our attention to input signals for nonlinear systems which are fixed a priori. Nevertheless it is a possible subject for further research to investigate active learning for nonlinear systems, which integrates the generation of an appropriate input signal in the identification process.

Relevant Inputs The next step is especially relevant for systems with multiple inputs and determines which of the available inputs affects which output. Though this step is of high importance for real world systems, the benchmark systems investigated contain only one input and one output signal, so that this step is not of such a high relevance for the investigation.

Dynamic Structure Furthermore the order of the delayed input and output signals used for the identification remains to be determined. Many approaches leave this choice to the user and for practical applications second order models are often argued to be *sufficient*. Nevertheless for a true automatic model generation from data the derivation of the relevant delayed values is necessary.

Structural Complexity The last three steps consider the structure of the nonlinear approximator. Structural complexity in this context means the complexity of the nonlinear approximator used. This can be the number of layers and neurons for a multilayer perceptron, the number of local models for a local model network or simply the number of basis function for a parametric approximator. There are several possible choices to determine the structural complexity, among the most common is Akaike's information criterion, cross validation or the validation on a separate validation data set.

High-Level Parameters Additionally parameters are divided in high-level and low-level parameters. This distinction corresponds to the fact that it makes a substantial difference, if a parameter can be obtained by applying the least squares method or if for the determination a nonlinear optimization process is necessary. Examples for high-level parameters are the hyperparameters of Gaussian process models or the nonlinear parameters in the HILOMOT split optimization routine.

Low-Level Parameters Low-level parameters can be obtained by applying least squares and are compared to high-level parameters relatively cheap to compute.

Many advanced system identification algorithms do not automatically consider all aforementioned steps. In practical applications the all remaining steps are left to the user. For example direct-weight optimization proposed in Roll et al. (2005) does consider the dynamic order of the system to be known. Nevertheless recently the dynamic order problem is incorporated in the automated routine by the usage of Gaussian process models as described by Pillonetto et al. (2011).

2.2 Nonlinear Approximator Framework

For the identification of nonlinear *dynamic* systems, the dynamics have to be represented and the nonlinearity has to be approximated. Three dynamic model structures are pursued here, see Section 2.3, all following the external dynamics approach depicted in Fig. 2. In this approach inputs and outputs are sent through an external filter bank followed by a nonlinear static approximator as described in Nelles (2001). In contrast to internal dynamics approaches there is no internal memory inside the nonlinear static approximator. The outputs of the external filter bank $\boldsymbol{\varphi}(k)$ serve as inputs for the nonlinear static approximator and the mapping from the filter outputs to the process output $\mathbf{y}(k)$ can be approximated by a static model.

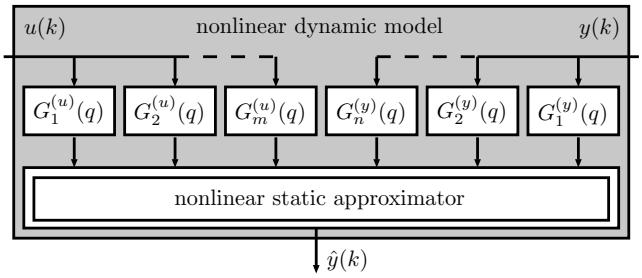

Fig. 2. External dynamics approach: External filter bank followed by a nonlinear static approximator.

Here, local model networks (LMNs) are used as the nonlinear static approximator for all dynamic structures. This model type follows a divide-and-conquer strategy. The whole input space, here spanned by the filter bank outputs $\boldsymbol{\varphi}(k)$, is divided into subregions. In each subregion a local model (LM) $\hat{y}_i$ is estimated. So called validity functions Φ_i define regions in which the LMs are valid and how interpolation between neighboring LMs should be conducted. According to Murray-Smith and Johansen (1995) the model output $\hat{y}$ of a LMN with M LMs is calculated by

$$\hat{y} = \sum_{i=1}^{M} \hat{y}_i(\boldsymbol{x})\Phi_i(\boldsymbol{z}) \text{ with}$$
$$\boldsymbol{x} \subseteq \boldsymbol{\varphi}(k) \text{ and } \boldsymbol{z} \subseteq \boldsymbol{\varphi}(k)\,. \tag{2}$$

As indicated in (2) the inputs for the LMs $\boldsymbol{x}$ and the inputs for the validity functions $\boldsymbol{z}$ are subsets of filter bank outputs $\boldsymbol{\varphi}(k)$. Note that the subsets $\boldsymbol{x}$ and $\boldsymbol{z}$ can be chosen independently, i.e. they can be completely distinct ($\boldsymbol{x} \cap \boldsymbol{z} = \emptyset$), identical ($\boldsymbol{x} = \boldsymbol{z}$) or anything in between.

Two well known algorithms are used in this work to train the LMNs, which are LOLIMOT (LOcal LInear MOdel Tree - Nelles and Isermann (1996)) and HILOMOT (HIerarchical LOcal MOdel Tree - Nelles (2006)). For details about the LOLIMOT and HILOMOT training procedures readers are referred to Nelles and Isermann (1996) and Nelles (2006), respectively.

2.3 Dynamic Structure Selection

Nonlinear AutoRegressive with eXogenous input (NARX) For the identification of nonlinear dynamic systems, the NARX structure is probably the most common. The transfer functions of the external dynamics (see Fig. 2) are simplified to:

$$G_i^{(u)}(q) = q^{-i}\,,\ i \in \{0,\ldots,m\}$$
$$G_i^{(y)}(q) = q^{-i}\,,\ i \in \{1,\ldots,n\}\,.$$