IDENTIFICATION OF NONLINEAR SYSTEMS

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Contents

Summary

This chapter presents an overview of the most important classes of nonlinear models and their practical methods of identification using measured input/output data. Since it is impossible to include all methods proposed in literature during the past three decades, only the most important methods for establishing parametric, nonparametric, semi-parametric and specific nonlinear models are discussed. The corresponding methods for identifying the parameters as well as the structure of nonlinear models are described. Finally these nonlinear identification methods are critically compared with one another in terms of some most important practical issues.

1. Introduction

The behavior of dynamic systems can be described by models. Such models are used for the purposes of

- prediction,
- explanation,
- process optimization,
- training process operators,
- fault detection,
- controller design
- etc.

Using a prediction model the energy consumption or product demand in technical systems can be forecasted. An explanation model can be applied to study the internal or external behavior of a critical technical or nontechnical system, especially in the case, when experiments cannot be conducted or are too expensive, such as a chemical reactor or a biological or economical system. For process optimization the real system is sometimes simulated by a dynamic model.

This model can be used under different operating conditions as a decision support for the operator or in training of process operators. Dynamic models are nowadays often used in fault detection, where the measured process behavior is compared with known models. The design of most modern control systems is based on dynamic models describing the input/output (I/O) behavior of the process to be controlled.

There are still other applications for dynamic models, as for example, in observers or filters for measuring states which cannot be measured directly, or models combined with intelligent sensors for reducing measuring time.

Dynamic models describing a dynamic system can be derived using *first-principles* of physics, chemistry, biology, economy etc. Because of the required special process knowledge these "physical" models are usually difficult to obtain. Furthermore, the complexity of most real systems, and the missing knowledge of many parameters leads to inaccurate models.

An alternative way to obtain a dynamic model is given by what is denoted as *system identification*, which aims at developing mathematical models for dynamic systems using measured I/O-data. Model building by system identification comprises the selection and processing of I/O-data for finding an appropriate model structure and providing the corresponding model description in parametric or nonparametric form.

Models obtained from system identification are called *black-box* models, whereas those derived from first-principles are also denoted as *white-box* models reflecting the complete physical insight about the corresponding real system, wherein all the parameters and variables are physically meaningful figures. Models which provide only partial physical insight about the real system are defined as *grey-box* models, and can be considered as a class of models existing between both extremes of white-box and black-box models.

This is, for example, the case when system identification is applied for determining only the parameters of a model whose structure is based on first-principles. Then the estimated model parameters may be often also interpreted in physical terms, which hold typically for a continuous-time model structure in the form of a differential equation.

However, there are other, similarly motivated models in which the model structure is first identified from the I/O-data in a black-box manner, using some generic model, e.g. differential or difference equations. Only after this initial black-box stage is the model interpreted in physical terms. Both types of modeling have similar objectives, but they can result in different models, and the latter often yields a better result.

The aim of system identification consists in developing a parametric or nonparametric model purely from measured I/O-data of a real system that reproduces the static and dynamic I/O-behavior of the latter subject to external influences as accurately as possible, even for the case of noise corrupted data. Nonlinear system models are usually rather complex. Due to the manifold forms in which nonlinear characteristics occur in real systems we also have a vast diversity of nonlinear model forms as discussed in this chapter. System identification involves following steps:

1) Data acquisition,
2) selection or determination of model structure,
3) parameter estimation,
4) validation of the identified model.

The *data acquisition* consists in selecting an appropriate input signal which should persistently excite the system over the whole range of operation during the experiment. Today usually digital measurement equipment is used. Therefore the sampling frequency of the I/O data has to be selected approximately 6 to 10-times the system bandwidth. For the selection of the input signal or input sequence two cases have to be considered:

- Only signals of normal operation of a system are allowed to be used.
- Application of specific test signals, as for example, a pseudo-random binary sequence (PRBS) for linear models and pseudo-random multi-level sequences (PRMLS) for nonlinear models is allowed.

The *model structure* can be obtained either from prior knowledge about the system or by application of specific statistical criteria. Often trial and error methods also provide an acceptable model structure. *Parameter estimation* provides the values of the unknown parameters in a parametric model structure.

Several methods are available which will be discussed later in more detail. Finally the *validation* of the identified model can be performed by simulating and evaluating the I/O behavior of the model applying as input signal a data set different from that used for the identification.

The identification steps discussed above represent usually some compromise between the expected model accuracy and the mathematical efforts necessary to obtain the model.

There are several categories of mathematical models to be distinguished:

- static and dynamic models,
- parametric and nonparametric models,
- continuous-time and discrete-time models,
- deterministic and stochastic models,
- lumped parameter and distributed parameter models,
- knowledge (or phenomenological) and representation models, and
- linear and nonlinear models.

Static mathematical models are applied to describe the steady-state or static I/O behavior of a system using the nonlinear static characteristic

$$y = f(u), \tag{1}$$

where *u* is the system input variable and *y* the corresponding output variable, respectively in the steady-state, and both are usually also dependent on time *t*. Table 1 includes some of the most important nonlinear static characteristics.

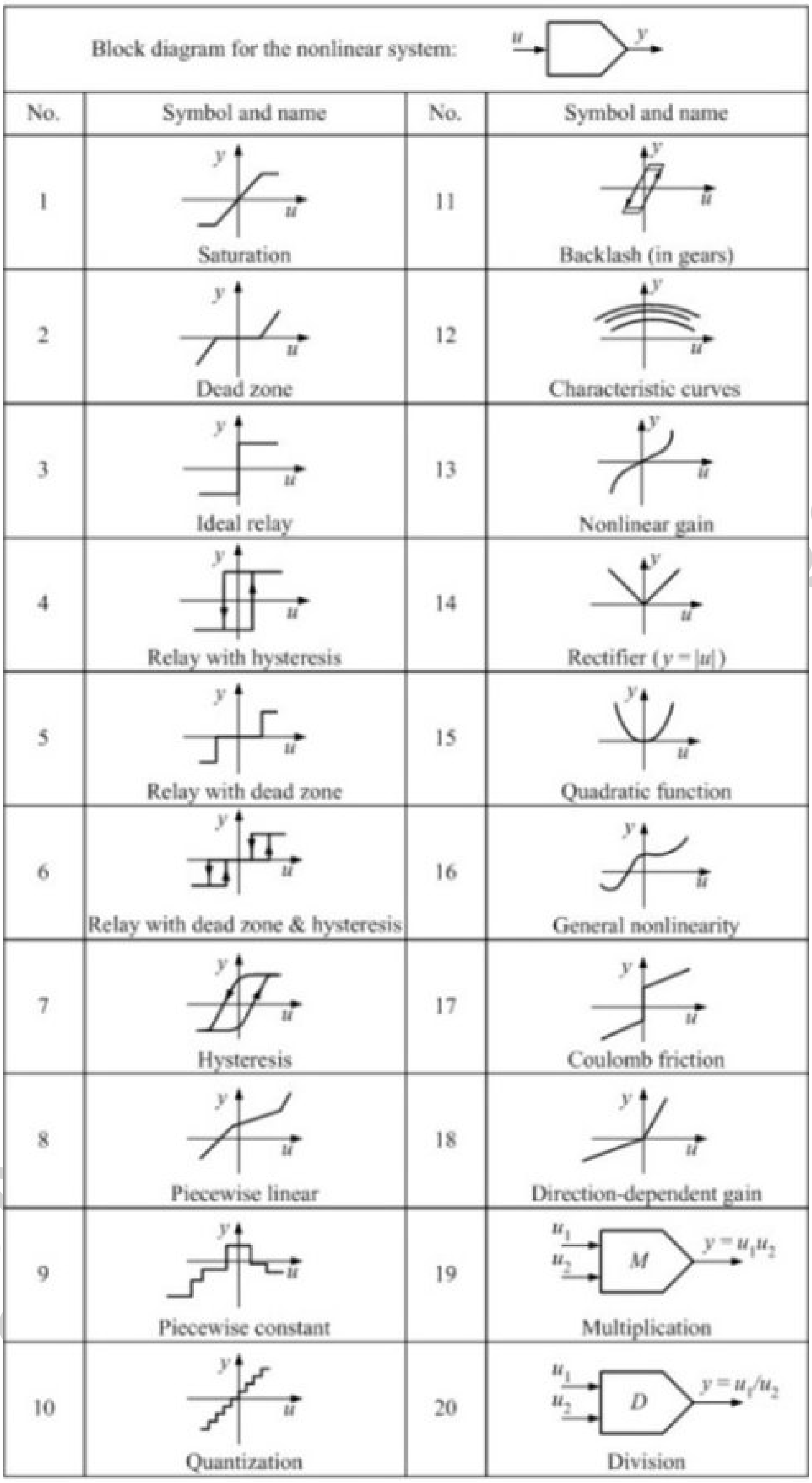

Table 1. Some typical nonlinearities

The dynamic behavior of a mathematical model can be characterized by a parametric, nonparametric or semi-parametric description. A *parametric model* is given, for example, either by

- a differential equation representing a *continuous-time model*,
- a difference equation representing a *discrete-time model*,
- a continuous or discrete state-space representation,

all having a linear or nonlinear structure, or in the linear case, by

- a transfer function $G(s)$ or a frequency response function $G(j\omega)$ for single input/single output (SISO-) systems or
- a transfer matrix $\mathbf{G}(s)$ for multi input/multi output (MIMO-) systems.

A *nonparametric model* is represented, for example, in a graphical or tabular form, such as curves or tables of step or impulse responses, frequency response plots, spectral distributions, integral kernels etc. In between the extreme forms of parametric and non-parametric models there are models which cannot strictly be included in any of these two classes and they have been denoted since more than a decade as *semi-parametric models*.

These models cover the recently emerging classes of models based on Fuzzy logic system (FLS) as well as neuro-fuzzy networks (NFN), both also allowing for the includsion of experimental human knowledge into the modeling process.

If a model of an undisturbed system can be obtained by applying a known and well-defined input signal, such as a step or ramp function, then it is denoted as a *deterministic model*. However, if the measured I/O-data of a system represent sequences of random variables, for example, caused by either measurement noise or uncontrollable unknown inputs, then the system can only be modeled by a *stochastic model* in which, as is normal, the estimated parameters are also stochastic variables, defined, for example, by the means and covariances (in the case of the ubiquitous Gaussian assumption).

The model realization then consists of stochastic partial models for the system and the disturbances.

Models described by ordinary differential equations relating their I/O behavior are usually defined as *lumped parameter models*, whereas models involving partial differential equations are denoted as *distributed parameter models*. Another, rather unconventional way for distinguishing models is to call those based on first-principles or phenomenological considerations as *knowledge models* and those derived from measured I/O-data *representation models*.

The distinction between *linear models* and *nonlinear models* is mainly based on the fact that for nonlinear models the principle of superposition does not hold. According to this principle a system model is called linear, if the response produced by the simultanous application of two (or more) different forcing functions at the input provides an output signal consisting of the sum of the two (or more) individual responses. There are also specific test methods that aim at detecting nonlinearities.

However, an easy and rough nonlinearity test exists in examining a scatter plot of the output $y(t)$ versus the input $u(t-T_d)$ in steady-state, where T_d represents the approximate delay between $u(t)$ and $y(t)$, which often can be estimated from some available a-priori knowledge. In low noise situations, such a scatter plot may already reveal important information about the nonlinearity.

Real-life systems are usually nonlinear and may also exhibit effects of time-varying and distributed parameters. These systems can often be approximated in a small range around a specific operating point by a linear model. In order to obtain a model for describing the whole operating range either a linear multi-model, consisting of a set of linear models each for a specific operating point often also denoted as local linear models, or more general *nonlinear models* should be applied.

There are nonlinear models of many types, such as I/O-models, state-space models, block-oriented models, convolution-type models etc. There is no general nonlinear model type available for all applications. Therefore the choice of the model type is dependent on each individual application. For the purpose of system identification, several modeling frameworks have been suggested. Various approaches for modeling and identification of nonlinear systems are divided according to Figure 1, into the following major groups:

- parametric models,
- nonparametric models,
- semi-parametric models and
- linear multi-models.

This contribution presents an overview of these nonlinear modeling approaches and compares them with one another in terms of practical aspects. This discussion can only address the main issues and the list of references is of course not complete, since only the most significant references can be included.

2. Parametric Models

Parametric models provide a very compact representation of dynamical systems in the form of difference or differential equations. Their parameters often have physical significance, especially in case of continuous-time systems. In this section, the most commonly used discrete-time and continuous-time parametric models will be considered. Besides very general models, models with special structures are often employed depending on the problem at hand.

In the case of discrete-time models usually the identification consists in establishing a black-box model, whereas for continuous-time modeling either a black-box model problem or more often a grey-box model problem has to be solved. During the last three decades a very rich mathematical framework for black-box modeling of linear systems has been established, and most of these techniques are also available in professional software packages, such as MATLAB. The last decade was especially characterized by a considerably increasing interest for nonlinear system identification.

However, it should be mentioned that nonlinear function approximation has already been of great interest in classical regression analysis of statistics since long time. Therefore this section will start with the very important class of parametric discrete-time regression models.

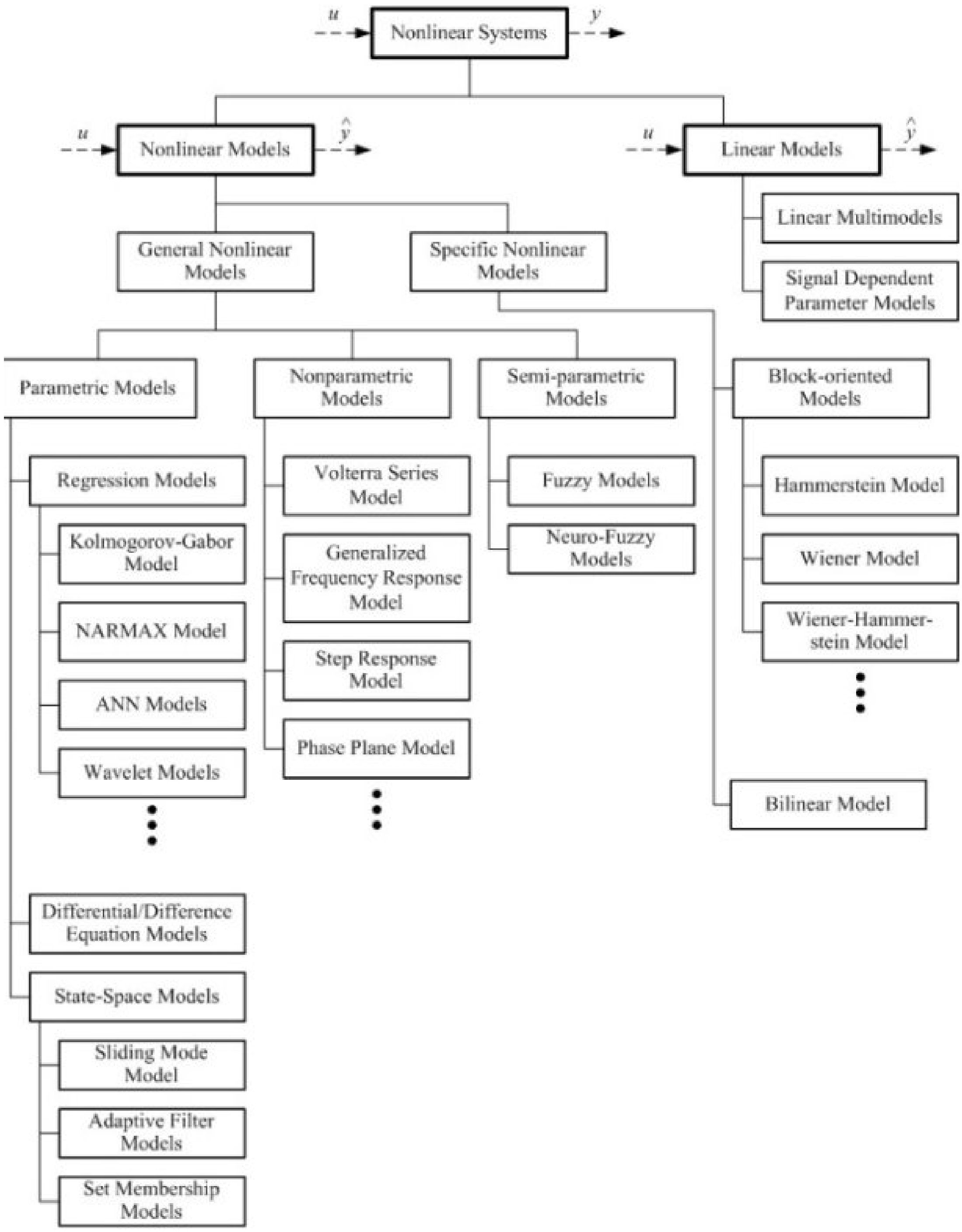

Figure 1: Most important nonlinear model structures

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