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Foreword

Dear Colleagues,

SCYR (Scientific Conference of Young Researchers) is a scientific event focused on exchange of information among young researchers from Faculty of Electrical Engineering and Informatics at the Technical University of Košice – series of annual events that was founded in 2000. Since 2000, the conference has been hosted by FEEI TUKE with rising technical level and unique multicultural atmosphere. The 22nd Scientific Conference of Young Researchers (SCYR 2022) was held on April 8, 2022. Due to COVID-19 pandemics, the conference was held online. The mission of the conference, to provide a forum for dissemination of information and scientific results relating to research and development activities at the Faculty of Electrical Engineering and Informatics, has been achieved. Approx. 70 participants, mostly by doctoral categories, were active in the conference.

Faculty of Electrical Engineering and Informatics has a long tradition of students participating in skilled labor where they have to apply their theoretical knowledge. SCYR is an opportunity for doctoral and graduating students to train their scientific knowledge exchange. Nevertheless, the original goal is still to represent a forum for the exchange of information between young scientists from academic communities on topics related to their experimental and theoretical works in the very wide spread field of a wide spectrum of scientific disciplines like informatics sciences and computer networks, cybernetics and intelligent systems, electrical and electric power engineering and electronics.

Traditionally, contributions can be divided in 2 categories:

- Electrical & Electronics Engineering
- Computer Science

with approx. 70 technical papers dealing with research results obtained mainly in the University environment. This day was filled with a lot of interesting scientific discussions among the junior researchers and graduate students, and the representatives of the Faculty of Electrical Engineering and Informatics. This Scientific Network included various research problems and education, communication between young scientists and students, between students and professors. Conference was also a platform for student exchange and a potential starting point for scientific cooperation. The results presented in papers demonstrated that the investigations being conducted by young scientists are making a valuable contribution to the fulfillment of the tasks set for science and technology at the Faculty of Electrical Engineering and Informatics at the Technical University of Košice.

We want to thank all participants for contributing to these proceedings with their high quality manuscripts. We hope that conference constitutes a platform for a continual dialogue among young scientists.

It is our pleasure and honor to express our gratitude to our sponsors and to all friends, colleagues and committee members who contributed with their ideas, discussions, and sedulous hard work to the success of this event. We also want to thank our session chairs for their cooperation and dedication throughout the entire conference.

Finally, we want to thank all the attendees of the conference for fruitful discussions and a pleasant stay in our event.

Liberios VOKOROKOS
Dean of FEEI TUKE

April 8, 2022, Košice

Contents

The Survey of Nonlinear Dynamical System Identification Methods

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***Abstract*—This survey provides an overview of the basic concepts, methods, and algorithms associated with the identification of nonlinear dynamical systems. It compares approaches of analytical and experimental identification in the context of white-box, grey-box, and black-box model structures. At the same time, it captures chronologically the system identification process from analytical identification to the validation of the obtained mathematical model. The main goal of my dissertation will be to create program modules for the identification of nonlinear dynamical systems.**

***Keywords*—Mathematical modeling, Nonlinear optimization, Parameter estimation, System identification**

I. Introduction

The goal of scientific research is to understand the world around us and to formally describe it using a generalized model [1]. Therefore, the purpose of the model is not necessarily to capture every detail of an object, but only the key aspects. In control engineering, the intention is to create a description of a dynamical system in the form of a mathematical model. This survey provides an overview of methods, structures, and algorithms associated with the identification of nonlinear dynamical systems. The individual sections are arranged according to the general system identification methodology. It starts with Section II, which describes the methods of analytical identification. Section III provides an overview of experimental identification methods, typical mathematical model structures, algorithms for parameter estimation, and the model validation procedure. The identification of the real (physical) system is dealt with in the final Section IV.

Presented methods, structures, and algorithms will be used in my dissertation thesis, which aims to develop and verify program modules to identify nonlinear dynamical systems. These program modules will be experimentally verified on laboratory plants with various dynamics available within the laboratories of the Center of Modern Control Techniques and Industrial Informatics (CMCT&II).

II. Mathematical modeling of Nonlinear Dynamical Systems

In our case, the subject of mathematical modeling is **dynamical systems**. A dynamical system is a real object that converts its inputs $\boldsymbol{u}$ into outputs $\boldsymbol{y}$. The output $\boldsymbol{y}$ of the system is functionally dependent on both the inputs $\boldsymbol{u}$ and the internal states $\boldsymbol{x}$ of the system. Thus, a dynamical system defines the evolution of system states $\boldsymbol{x}$ with respect to an independent variable (usually time t).

A **model** is an abstraction of a real system that describes the relationships between inputs $\boldsymbol{u}$ and outputs $\boldsymbol{y}$ of a system. The most common system representation is a **mathematical model** with input-output relationships expressed using mathematical functions. In addition, other forms of model representation exist, such as *tables* or *graphs*.

Systems can be classified into several groups based on their properties [2]. Based on the system variable types, the following classification applies:

- **Continuous:** The state values $\boldsymbol{x}$ change continuously over time $t \in \mathbb{R}$ and the system is described by differential equations.
- **Discrete:** The state values $\boldsymbol{x}$ change at discrete time intervals $k \in \mathbb{Z}$ and the system is described by a difference equation.
- **Hybrid:** Combines multiple continuous and/or discrete system dynamics that changes abruptly based on discrete events.

Systems can also be categorized according to mathematical operations that describe their input-output properties:

- **Linear:** Dependencies within the system can be described using linear functions, or their linear combination.
- **Nonlinear:** The system description consists of nonlinear functions or a nonlinear combination of functions. Real systems exhibit nonlinear behavior and thus we will solely focus on them.

Based on properties of model parameters:

- **Time-invariant:** Parameter values are fixed or their changes are insignificant.
- **Time-variant:** Parameter values evolve over time or change based on the system states.

Mathematical modeling is a set of techniques and methods with the aim to create a mathematical model of a system. The general form of the mathematical model in the state-space representation is given in (1), where $\boldsymbol{f}$ and $\boldsymbol{g}$ are arbitrary mathematical functions.

$$\begin{aligned} \dot{\boldsymbol{x}}(t) &= \boldsymbol{f}\left(\boldsymbol{x}(t), \boldsymbol{u}(t)\right) \\ \boldsymbol{y}(t) &= \boldsymbol{g}\left(\boldsymbol{x}(t), \boldsymbol{u}(t)\right) \end{aligned} \tag{1}$$

The aim of mathematical modeling is to identify these two functions ($\boldsymbol{f}$ a $\boldsymbol{g}$) using physics laws. As the system can be quite complex, it is better to split it into simpler components. These can be modeled separately and subsequently connected together to obtain the overall model [3]. Standard techniques such as impedance modeling, balance equations, or Lagrange equations can also be used. The resultant model structure is the so-called *white-box model*. The advantage of this approach is that the obtained model is parametric and the parameters have a physical interpretation. The problem arises when parameter values could not be directly measured or read from datasheets. Another disadvantage is the fact that many physical laws and equations are based on the assumptions of an *ideal environment*. These approximations may not be accurate enough in every application. Stated shortcomings of the white-box model can be mitigated by performing appropriate experiments on a real system and their subsequent analysis. Such an approach is called **experimental identification**.

III. Methods of Nonlinear System Identification

System identification is an iterative process that aims to obtain a mathematical model of the system from experimental data. More precisely from the measurable inputs $\boldsymbol{u}$ and outputs $\boldsymbol{y}$ of the observed system. The identification process can be divided into several steps [4] that are repeated when necessary:

- **Experiment design:** An initial step in which it is necessary to apply all a priori knowledge about the observed system to design an experiment, as improper design may lead to the destruction of the real system. In addition to the experiment design, this point also includes the collection of data from the system, where the set of available sensors, the method of data recording, the sampling period T_s, etc. must be taken into account. It is important to note that even though the system is continuous, the recorded data is in discrete form. This fact plays an important role in continuous model identification.
- **Structure selection:** The mathematical model can have different shapes and sizes, and the individual parameters could also have different physical interpretations in various structures. The model structure and consequently the number of parameters is closely tied to the *model complexity*. More complex models usually approximate the real system better but are associated with higher computational cost and more complex parameter estimation algorithms.
- **Parameter estimation:** This is a step in which the selected model structure adapts to the measured data by changing the parameter values. Parameter estimation is closely linked to statistical and optimization methods [5].
- **Model validation:** The last step of system identification is to verify that the identified mathematical model meets its expectations. The purposes of the mathematical models are diverse (digital twin, design of control laws, etc.) and therefore it is not possible to rely solely on qualitative or quantitative evaluation.

According to the selected model structure, the identified models can be divided into two main categories: *grey-box* and *black-box*. In the case of grey-box models, the model's structure is predetermined and only the parameters are identified. On the contrary, in the case of the black-box model both parameters and structure are identified simultaneously. In both cases, the approximation model of the system is modified according to the output prediction error $\boldsymbol{e}(k)$, (2).

$$\boldsymbol{e}(k) = \boldsymbol{y}(k) - \hat{\boldsymbol{y}}(k) \tag{2}$$

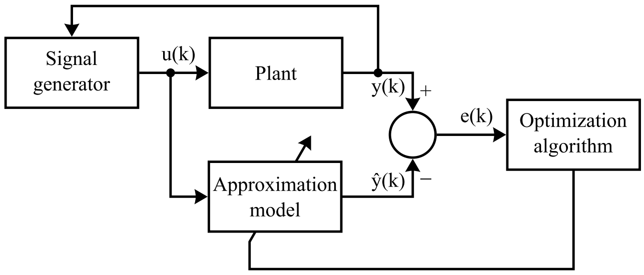

Fig. 1. General schema of system identification loop driven by output prediction error [6].

where: $\boldsymbol{e}(k)$ - output prediction error
$\boldsymbol{y}(k)$ - output of real system
$\hat{\boldsymbol{y}}(k)$ - output of approximation model

With the addition of a proper optimization algorithm, the identification structure in Fig. 1 can be used for both the online and the offline identification tasks.

A. Grey-box System Identification

Grey-box model system identification methods can be further subdivided according to whether they lean more towards white-box or black-box models. The resulting division, named by the author of [1], is called a *model's palette of grey shades*:

- **Off-white models** are derived from white-box models and the subject of identification is the parameter vector $\boldsymbol{\theta}$. This method can be challenging especially if the mathematical model (1) includes complicated functions.
- **Smoke-grey models** seek to effectively eliminate nonlinear properties of real systems and thus enabling the system to be identified in a linear structure. For this, nonlinear transformations of the measured data are used. These transformations could be based on the physical nature of the system. The described procedure is sometimes referred to as the feedback linearization method [7].
- **Steel-grey models** are based on the idea that nonlinear systems can be approximated by linear ones within the close vicinity of the operation area. By combining several linear models, it is possible to obtain one composite model that describes the dynamics of the nonlinear system. By modification of the composite model formulation, it is possible to obtain a linear time-variant model.
- **Slate-grey models** are the last stage before the black-box models. Block-oriented models are a good example of this category, where the structure of the system is composed of functional blocks. Two types of blocks are used: linear dynamical systems and static nonlinear transformations. The exact choice of suitable nonlinear transformations can also have a physical basis.

Methods based on system identification in the form of a grey-box model require designing the structure of the model. This is laborious from the user's perspective as it requires a lot of experimentation and practical experience.

B. Black-box System Identification

The use of black-box models makes it possible to identify dynamical systems without the need to define the exact structure. The structure is created automatically during the identification process using an optimization algorithm [4]. Therefore, these methods are being referred to as data-driven methods. In (3) the general mathematical form of the model is given. The function $\boldsymbol{f}$ represents a model consisting of both the parameters and the structure of the identified system.

$$\hat{\boldsymbol{y}}(k+1) = \hat{\boldsymbol{f}}\big(\boldsymbol{y}(k), \boldsymbol{y}(k-1), ..., \boldsymbol{y}(k-n), \boldsymbol{u}(k), \boldsymbol{u}(k-1), ..., \boldsymbol{u}(k-m)\big) \tag{3}$$

This notation is used because the internal states and the parameters have no physical significance. The black-box mathematical model is usually discrete, as it was created based on experimental data obtained at discrete time intervals.

In terms of nonlinear identification in the form of a black-box model, **neural networks** are dominant category of machine learning (ML) methods. This choice is motivated by the fact that neural networks are considered a universal approximator of any mathematical function. Ignoring the random noise present in the real systems, this property is a sufficient precondition for building a system model. The most used black-box model structures are [4]:

- **Multilayer Perceptron** combined with the backpropagation optimization algorithm is one of the simplest neural network applications. In the system identification context, it provides satisfactory results, while drawbacks are associated mainly with parameter convergence, computational complexity, and the local minimum problem [8].
- **Radial Basis Function Neural Network** is a special case of a neural network with a single hidden layer that uses the Gaussian function as an activation function. The learning is split in two phases: first, the parameters of the Gaussian functions are estimated; second, the synaptic weights are estimated. The idea behind the use of the Gaussian function is to divide the nonlinear workspace into smaller areas [9] that can be described linearly.
- **Functional Link Network** uses hardcoded nonlinear input transformations to linearize the workspace.
- **Time Delay Network** has an input layer extended by historical inputs $\boldsymbol{u}$ and outputs $\boldsymbol{y}$ of the system. This makes it possible to better represent the current state of the system, which subsequently helps to improve prediction accuracy. Time Delay Network is a key concept of dynamical system identification.
- **Recurrent Neural Network** contains recurrent connections that allow the neural network to maintain the previous state of the system [10] similar to the Time Delay Network. The system state is maintained internally so there is no need to modify the input layer. An improvement to recurrent neural networks is the Long Short-Term Memory (LSTM) model, which allows longer retention of system status [11]. Recurrent networks are often associated with the stability problem.
- **Wavelet Neural Network** is an architectural design in which the activation functions of the first hidden layer are replaced by a wavelet transform. This allows for better analysis of signal properties [12] and consequently partial elimination of nonlinear properties.
- **Temporal Convolutional Network** is one of many applications of a relatively new machine learning paradigm called *Deep Learning*. Thanks to the deep and complex structures, it combines the advantages of the above approaches. The main advantage of deep learning is the automatic feature extraction from the data that makes it a very flexible structure for dynamical system identification. Authors in [13] compared this approach with *Multilayer Perceptron* and *LSTM* structures and experimentally proved its potential in system identification.

In addition to the mentioned structures of neural networks, it is possible to identify systems using other ML methods or their combinations [14]. Popular are neuro-fuzzy methods, genetic algorithms, Swarm Intelligence, etc. Although black-box models provide high flexibility in the task of system identification, their structure is often too complicated to be properly analyzed using classical methods of systems analysis.

C. Parameter estimation algorithms

Up until now, this section was focused on methods and structures of system identification. The remaining unanswered question is how to determine the values of the mathematical model's parameter vector $\boldsymbol{\theta}$. Values estimation can be formulated as an *optimization task*, that is formally written in (4).

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \sum_{i=1}^{N} \boldsymbol{e}^T(i, \boldsymbol{\theta})\boldsymbol{e}(i, \boldsymbol{\theta}) \tag{4}$$

where: $\hat{\boldsymbol{\theta}}$ - estimated parameter vector
N - number of samples

The stated task can be solved using various optimization algorithms. To make this section cleaner, we are going to list only a few of the most prevalent optimization algorithms used for dynamical system identification:

- **Gauss-Newton least squares** is a standard algorithm for the nonlinear estimation of function parameters. It is based on the assumption that the error function is a quadratic function.
- **Steepest descent** algorithm is known for estimating neural network parameters and is based on a function's gradient calculation. The values of the parameter vector $\boldsymbol{\theta}$ are literally shifted in the *downhill* direction of the gradient in each iteration.
- **Levenberg-Marquardt least squares** is an algorithm combining principles of both the Gauss-Newton and the Steepest descent algorithms. In the vicinity of optimal parameter values, it behaves similarly to Gauss-Newton and at greater distances as Steepest descent [15].
- **Evolutionary computing** is inspired by optimization observed from nature. The main advantage of this algorithm is the lower susceptibility to stuck in the local optimum, as the searched space is relatively widely covered.

The choice of the optimization algorithm is closely linked to the choice of the model structure. A combination of different algorithms or their modification can make the optimization task faster and more reliable.

Apart from the selection of optimization algorithms, the initialization of the parameter vector $\boldsymbol{\theta}$ is also important. In the case of grey-box models, where the parameters have their physical significance, it is possible to *estimate* values of unknown parameters by hand. In the case of black-box models, *random initialization* is used, as there is no connection between parameter values and the real world.

D. Model validation

The last part of the systems identification process is the validation of the identified mathematical model. The mathematical model can be validated in an open-loop or in a closed-loop. In both cases, the output of the real system is compared

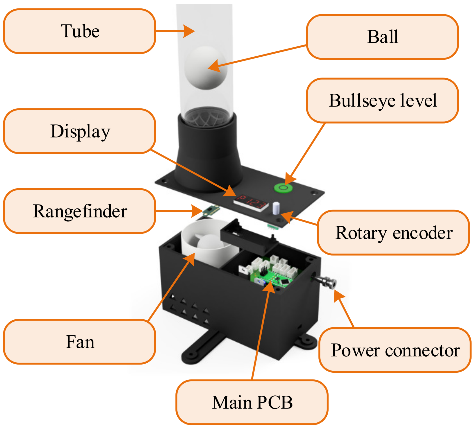

Fig. 2. Component assembly of the Aerodynamic Ball Levitation Laboratory Plant [6]. See: http://kyb.fei.tuke.sk/laboratoria/modely/al.php

with the output of the mathematical model. Historically, model validation has often been overshadowed by the identification methods [16]. Therefore, subjective evaluation methods like *by eye inspection* were mainly used to compare the outputs. From the model validity evaluation standpoint, this is still a common method [4]. The drawback of this method is sole reliance on the expert's judgment. For this reason, it is more appropriate to rely on **quantitative evaluation methods** instead. A *fit ratio* is usually used for this task. Apart from the possibility to generate negative values, it is also sensitive to the signal amplitude in the case of non-normalized values. The authors in [17] presented a modification of this method that internally uses normalization as the solution for these problems. Lastly, part of the model validation is to verify whether the model meets the author's expectations, e.g. whether it allows the design of suitable control laws.

As part of my dissertation thesis, I will use the identified mathematical model for control law design. The validation of the model will therefore be performed mainly in the closed-loop control structure.

IV. Identification of Aerodynamic Ball Levitation Laboratory Plant

Methods and techniques presented in this survey were used in our article [6] focused on the construction, mathematical modeling, experimental identification, and control of the physical dynamical system of aerodynamic levitation shown in Fig. 2. As part of analytical identification, a mathematical model was derived in the form of a system of nonlinear differential equations. Since not all parameters of the model were directly measurable, it was necessary to proceed to experimental identification. The resulting structure of the obtained model was a grey-box model. This model has been used to design control laws that were later verified in the simulation environment. Finally, control laws were applied to the real system and the outputs were compared with the simulation. The obtained results were evaluated both qualitatively and quantitatively. In conclusion, the obtained mathematical model was able to appropriately approximate key parts of the real system's dynamics. This plant will be further used in research activities of CMCT&II.

V. Conclusion

The presented survey provides an overview of key methods, structures, and algorithms used in the identification of nonlinear dynamical systems. It also compares approaches of analytical and experimental identification. I will use the presented knowledge in my dissertation thesis in the design of program modules to identify nonlinear dynamical systems. These program modules will be experimentally verified on models of physical systems at CMCT&II. In addition to our research group, the authors will explore the possibility of applying these program modules and methodology to solve modeling and identification tasks of hybrid systems in the *ALICE Experiment* at CERN that both authors are associated members of.

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