WORKSHOP ON NONLINEAR SYSTEM IDENTIFICATION BENCHMARKS

5TH EDITION, EINDHOVEN, THE NETHERLANDS, APRIL 22-23, 2021

PROGRAM

THURSDAY 22/04/2021

14.00 – 14.05	Welcome & Introduction	
14.05 – 15.20	Session 1	Marco Forgione, Manas Mejari and Dario Piga - **dynoNet: A neural network architecture for learning dynamical systems.** Gerben I. Beintema, Roland Tóth, Maarten Schoukens - **Nonlinear state-space identification using sub-space encoders: A Wiener-Hammerstein case-study.** Tim Decker, Hiren Patel, Max Schussler and Oliver Nelles - **Neural Networks with different Dynamics Realizations for the Bouc-Wen Benchmark Problem.**
15.20 – 15.35	Break	
15.35 – 16.25	Session 2	Johannes N. Hendriks, Fredrik K. Gustafsson, Antonio H. Ribeiro, Adrian G. Wills and Thomas B. Schön - **Deep Energy-Based NARX Models.** Timothy J. Rogers, Tobias Friis, Keith Worden, Elizabeth J. Cross - **Gaussian Process Latent Nonlinear Restoring Force Identification of The Silverbox.**
16.25 – 16.40	Break	
16.40 – 17.30	Session 3	Konstantinos Vlachas, Konstantinos Agathos, Konstantinos Tatsis, Adam R. Brink and Eleni N. Chatzi - **Two-story frame with Bouc-Wen hysteretic links as a multi-degree of freedom nonlinear response simulator.** Mahmoud Elkafafy, Lorenzo Lugo, Lorenzo Signori, Bram Cornelis, Theo Geluk, and Karl Janssens. **Detection, understanding, and localization of nonlinearities in a vehicle suspension system.**
17.30 – 18.00	Discussion	

All times are following the Amsterdam time.

FRIDAY 23/04/2021

14.00 – 14.05	Introduction	
14.05 – 15.20	Session 4	Johan Schoukens and Jan Decuyper - **A bird's eye perspective on decoupling in Black Box Nonlinear System Identification.** Péter Z. Csurcsia, Jan Decuyper, Johan Schoukens and Tim De Troyer - **Empirical study on decoupling PNLSS models illustrated on F16.** Ridvan Karagoz and Kim Batselier - **Nonlinear system identification with regularized Tensor Network B-splines.**
15.20 – 15.45	Break	
15.45 – 17.00	Session 5	Elizabeth J. Cross, Matthew R. Jones, Weijiang Lin, Rajdip Nayek, Daniel J. Pitchforth and Timothy J. Rogers. **Grey-box benchmarks system identification with Gaussian processes**. L. Cristian Iacob, Gerben I. Beintema, Maarten Schoukens and Roland Tóth. **Deep Identification of Nonlinear Systems in Koopman Form.** Antonio H. Ribeiro, Johannes N. Hendriks, Adrian G. Wills and Thomas B. Schön - **Beyond Occam's Razor in System Identification: Double-Descent when Modeling Dynamics.**
17.00 – 17.30	Closing & Discussion	

All times are following the Amsterdam time.

SHORT ABSTRACTS

1. Marco Forgione, Manas Mejari and Dario Piga. **dynoNet: A neural network architecture for learning dynamical systems.**

In this presentation we introduce dynoNet, a novel neural network architecture tailored for system identification purposes which utilizes linear time-invariant (LTI) transfer functions as elementary building blocks. In a dynoNet, the LTI blocks are arbitrarily interconnected with static non-linearities such as elementary activation functions, feed-forward neural networks, or other differentiable operators (e.g., polynomials). Efficient formulas defining the back-propagation behavior of the linear transfer function for automatic derivative computations are devised. This enables convenient end-to-end training of dynoNet models using common deep learning software. Examples show the effectiveness of the proposed methodologies on standard system identification benchmarks.

https://doi.org/10.1002/acs.3216

2. Gerben I. Beintema, Roland Tóth, Maarten Schoukens. **Nonlinear state-space identification using sub-space encoders: A Wiener-Hammerstein case-study.**

In short, the proposed method utilizes a sub-space encoder formulated using neural networks which estimates the initial state based on past inputs and output. Multiple initial state estimates are used to formulate a computationally performant multi-step-ahead cost function which enables state-of-the-art benchmark performances. In this presentation, I will illustrate the proposed sub-space encoder method on the Wiener-Hammerstein benchmark. Moreover, the presented method also performs well on other vastly different identification problems such as modelling the dynamics of a ball directly from video footage.

https://arxiv.org/abs/2012.07697

3. Tim Decker, Hiren Patel, Max Schussler and Oliver Nelles. **Neural Networks with different Dynamics Realizations for the Bouc-Wen Benchmark Problem.**

Artificial neural networks have proven to be powerful approximators for nonlinear systems. At the same time, finite impulse response (FIR) and infinite impulse response (IIR) filters are alternative linear dynamic model structures. In this paper different dynamics realizations are combined with various neural network architectures to the Bouc-Wen benchmark problem.

Extended abstract

4. Johannes N. Hendriks, Fredrik K. Gustafsson, Antonio H. Ribeiro, Adrian G. Wills and Thomas B. Schön. **Deep Energy-Based NARX Models.**

This paper is directed towards the problem of learning nonlinear ARX models based on system input–output data. In particular, our interest is in learning a conditional distribution of the current output based on a finite window of past inputs and outputs. To achieve this, we consider the use of so-called energy-based models, which have been developed in allied fields for learning unknown distributions based on data. This energy-based model relies on a general function to describe the distribution, and here we consider a deep neural network for this purpose. The primary benefit of this approach is that it is capable of learning both simple and highly complex noise models, which we demonstrate on simulated and experimental data.

https://arxiv.org/pdf/2012.04136.pdf

5. Timothy J. Rogers, Tobias Friis, Keith Worden and Elizabeth J. Cross. **Gaussian Process Latent Nonlinear Restoring Force Identification of The Silverbox.**

Restoring force surface methods are one of the classic tools in nonlinear system identification of mechanical systems, by considering the difference between the inertial forcing in the system and the applied external loading a function can be fit in a parametric or nonparametric manner to model the internal restoring forces of a (nonlinear) oscillator. However, to fit this function full access to the internal states of the system is required, i.e. the displacement and velocity. While numerical techniques for integration or differentiation of measured signals can give estimates of these (usually) unknown quantities, the presence of measurement noise on the signal can lead to poor estimates. This in turn complicates the fitting of the nonlinear function which is the restoring force of the system. This work will discuss a new approach which couples the ideas of the restoring force surface with a Bayesian filter which models the unknown linear dynamics and the nonlinear restoring force. A Gaussian process in time is adopted which models the unknown contribution of the nonlinear terms in the equations of motion, this allows probabilistic estimation of the unknown internal states (displacement and velocity) as well as a nonparametric estimate of the missing "force" due to the presence of the nonlinearity. The proposed technique is demonstrated on the Silverbox benchmark and some of the limitations are discussed alongside the successes in identification.

6. Konstantinos Vlachas, Konstantinos Agathos, Konstantinos Tatsis, Adam R. Brink and Eleni N. Chatzi. **Two-story frame with Bouc-Wen hysteretic links as a multi-degree of freedom nonlinear response simulator.**

A diverse variety of engineering and dynamic systems, ranging from control applications and solid mechanics to biology and economics, feature hysteretic phenomena. This commonly encountered nonlinear behavior can be captured and described via diverse numerical models, with the Bouc-Wen representation comprising a common choice within the nonlinear dynamics and vibration engineering community. In this benchmark, the Bouc-Wen model is employed to characterize the response of the nodal connections of a two-story frame structure. The resulting shear frame with hysteretic links is proposed as a multidegree of freedom nonlinear response simulator. This case study can be seen as an extension to the single degree of freedom 'Hysteretic Benchmark with a Dynamic Nonlinearity' problem already featured in the nonlinear benchmark website (http://www.nonlinearbenchmark.org/). Our simulator employs a similar parameterized representation of the Bouc-Wen model for each nonlinear link and builds upon it to also include strength deterioration and stiffness degradation effects in a structure with increased dimensionality. As a result, the featured parametric shear frame serves as a multi-degree of freedom nonlinear response simulator, able to model a wide range of nonlinear effects through the parametrized Bouc-Wen couplings. The provided simulator can be utilized as a benchmark problem to validate methods and tools in structural health monitoring, model reduction, or identification applications.

Extended abstract

7. Mahmoud Elkafafy, Lorenzo Lugo, Lorenzo Signori, Bram Cornelis, Theo Geluk, and Karl Janssens. **Detection, understanding, and localization of nonlinearities in a vehicle suspension system.**

In automotive industry, a robust and reliable objective quantification of the vehicle performance is needed in order to reduce the cost and shorten the vehicle dynamics design process, which involves analyzing different design variants. One key criterion on which the automotive manufacturers rely when evaluating the performance of a new designed vehicle is the human perception of the designed vehicle's ride and handling performance. This human perception of ride and handling can be adversely affected by the nonlinear behavior of a certain vehicle component. Methodologies to quantify, understand and localize the nonlinear behavior of vehicle subcomponents will certainly help in reducing the costs and shorten the design cycle of a new vehicle.

In this contribution, using data measured on a real (simplified) quarter-car suspension system in laboratory condition, the detection and localization of friction and damping nonlinearities in such subsystem of the vehicle will be illustrated. An electro-mechanical shaker was used to excite the suspension system with a random 'odd' multisine signal. Such dedicated signal enables the distinguishing between the friction and damping nonlinearity by looking at the odd and even frequency lines. In the frame of this study, the so-called 'Reverse Path' spectral method was used to localize the source of the dominant nonlinearity in the system.

8. Johan Schoukens and Jan Decuyper. **A bird's eye perspective on decoupling in Black Box Nonlinear System Identification.**

A major choice in nonlinear system identification is the selection of a white (grey) or a (pit) black modeling approach. Black box identification is a very flexible and generic approach that comes with the price of an (extremely) large number of model parameters and a lack of physical insight. For that reason the white box approach is often preferred whenever the higher modeling effort can be afforded. Recently, numerical methods were developed that allow to decompose multivariate polynomials $\boldsymbol{q} = f(\boldsymbol{p})$ in a decoupled form $\boldsymbol{q} = Wg(V^T\boldsymbol{p})$, with W, V linear transformations, and g a univariate function ($g_i(\boldsymbol{x}) = g_i(x_i), i = 1, \dots, r$, with $\boldsymbol{x} = V^T\boldsymbol{p}$. In this presentation we will give a bird's eye perspective on how these new tools remove/reduce the major disadvantages of black box modeling significantly so that at the end of the modeling process a sparse nonlinear model is obtained. By simplifying the model structure, reducing the number of model parameters, and revealing underlying physical structures, the decoupling approach provides a versatile bridge between the flexibility of black box system identification and the high structural insight of white or grey modeling approaches. This can be a game changer that combines the advantages of black and white box modeling without heritating the intrinsic disadvantages of both approaches.

Extended abstract

9. Péter Z. Csurcsia, Jan Decuyper, Johan Schoukens and Tim De Troyer. **Empirical study on decoupling PNLSS models illustrated on F16.**

This work illustrates a combined nonparametric and parametric system identification framework for modeling nonlinear vibrating structures. First step is the analysis: multiple-input multiple-output measurements are (semi-automatically) preprocessed, and a nonparametric Best Linear Approximation (BLA) method is performed. The outcome of the BLA analysis results in nonparametric (BLA) FRF, noise and nonlinear distortion estimates. Based on this information, a linear parametric (state-space) model is built. This model is used to initialize a high complexity Polynomial Nonlinear State-Space PNLSS model. The nonlinear part of a PNLSS model is manifested as a combination of high-dimensional multivariate polynomials. The last step in the proposed approach is the decoupling: transforming multivariate polynomials into a simplified, alternative basis, thereby dramatically reducing the number of parameters. In this work a novel filtered canonical polyadic decomposition (CPD) is used. The proposed methodology is illustrated on, but of course not limited to, a ground vibration testing measurement of an air fighter.

10. Ridvan Karagoz and Kim Batselier. **Nonlinear system identification with regularized Tensor Network B-splines.**

Multivariate B-splines suffer from the curse of dimensionality, i.e. the number of weights that define a B-spline tensor product surface grows exponentially with the number of input dimensions. This limits the application of B-splines in nonlinear system identification. Tensor network theory provides a mathematical framework to elleviate the curse of dimensionality by representing a high dimensional tensor as a low-rank approximation. Optimization algorithms in the tensor network format allow the estimation of the exponentially large weight tensor of multivariate B-splines, without ever needing explicit construction. We present and validate the Tensor Network B-spline model through the identification of the Cascaded watertank and Bouc-Wen benchmarks using a NARX approach.

Extended abstract

11. Elizabeth J. Cross, Matthew R. Jones, Weijiang Lin, Rajdip Nayek, Daniel J. Pitchforth and Timothy J. Rogers. **Grey-box benchmarks system identification with Gaussian processes.**

This work seeks to incorporate one's partial knowledge into inference over a system. Here a Gaussian process in various forms will be employed to account for unknowns contributing to a systems' response. We pursue a number of architectures on the grey spectrum, building differing levels of insight in through design of the covariance function. The case studies investigated here are the Electro-Mechanical Positioning System and Silverbox benchmarks.

12. L. Cristian Iacob, Gerben I. Beintema, Maarten Schoukens and Roland Tóth. **Deep Identification of Nonlinear Systems in Koopman Form.**

This presentation treats the identification of nonlinear dynamical systems using Koopman-based deep subspace encoders. Through this method, the usual drawback of needing to choose a dictionary of lifting functions a priori is circumvented. The encoder represents the lifting function to the space where the dynamics are linearly propagated using the Koopman operator. An input-affine formulation is considered for the lifted model structure and we address both full and partial state availability. The framework is implemented using and extending the capabilities of the deepSI toolbox. Due to the high computation cost of minimizing the simulation error, the data is split into subsections where multi-step prediction errors are calculated independently. This formulation allows for efficient batch optimization tuning of the network parameters. Moreover, we obtain excellent long-term prediction capabilities of the obtained models due to the truncated simulation error cost that is estimated.

13. Antonio H. Ribeiro, Johannes N. Hendriks, Adrian G. Wills and Thomas B. Schön. **Beyond Occam's Razor in System Identification: Double-Descent when Modeling Dynamics.**

System identification aims to build models of dynamical systems from data. Traditionally, choosing the model requires the designer to balance between two goals of conflicting nature; the model must be rich enough to capture the system dynamics, but not so flexible that it learns spurious random effects from the dataset. It is typically observed that model validation performance follows a U-shaped curve as the model complexity increases. Recent developments in machine learning and statistics, however, have observed situations where a "double-descent" curve subsumes this U-shaped model-performance curve. With a second decrease in performance occurring beyond the point where the model has reached the capacity of interpolating – i.e., (near) perfectly fitting – the training data. To the best of our knowledge, however, such phenomena have not been studied within the context of the identification of dynamic systems. The present paper aims to answer the question: "Can such a phenomenon also be observed when estimating parameters of dynamic systems?" We show the answer is yes, verifying such behavior experimentally both for artificially generated and real-world datasets.

https://arxiv.org/pdf/2012.06341.pdf