2013 European Control Conference (ECC)
July 17-19, 2013, Zürich, Switzerland.

Three free data sets for development and benchmarking in nonlinear system identification

Torbjörn Wigren, *Senior Member, IEEE,* and Johan Schoukens, *Fellow, IEEE*

***Abstract*—System identification is a fundamentally experimental field of science in that it deals with modeling of system dynamics using measured data. Despite this fact many algorithms and theoretical results are only tested with simulations at the time of publication. One reason for this may be a lack of easily available live data. This paper therefore presents three sets of data, suitable for development, testing and benchmarking of system identification algorithms for *nonlinear* systems. The data sets are collected from laboratory processes that can be described by block – oriented dynamic models, and by more general nonlinear difference and differential equation models. All data sets are available for free download.**

I. Introduction

THE field of non-linear system identification is progressing rapidly today, with several algorithms being available in standard software packages like the MATLAB™ System Identification Toolbox developed by L. Ljung [1]. That toolbox e.g. supports discrete time black-box methods based on nonlinear ARX models [2], neural networks [3], and block-oriented models [4]. It also handles grey-box models and algorithms [5], and provides means for data interfacing. At the same time applications are reported from many fields, including e.g. chemical engineering [6], solar power generation [7], biomedicine [8], and communications [9]. Although many practical system identification problems can admittedly be solved with existing software packages like [1], the research on algorithms for identification of nonlinear dynamic systems is very active today, with many remaining unsolved problems.

The development and characterization of such new algorithms are challenging tasks. Simulation and theoretical analysis are two standard tools used in this development [10], [11]. The use of measured data is reported more seldom though, although some such data has been made publicly available [12], see the IFAC website http://tc.ifac-control.org/1/1/Data%20Repository/sysid-2009-wiener-hammerstein-benchmark, Measured data is also available from the SISTA identification database DaISy [13], see http://homes.esat.kuleuven.be/~smc/daisy/daisydata.html. The far too low usage of this material is regrettable, since lack of testing against real data may result in a too poor robustness, and algorithms that are not suitable for the operating conditions encountered in practical applications.

The main purpose of this paper is therefore to emphasize the importance of the subject, by a discussion of properties of benchmarking data for *nonlinear* system identification. The main contribution of the paper is then presented in terms of three sets of data that are believed to be suitable for development, characterization and benchmarking of nonlinear system identification algorithms and tools. The data sets are available for free download. The first set of data is recorded from the so called coupled electric drives [14], [15]. The speed control dynamics of that laboratory process can be accurately modeled by a nonlinear dynamic Wiener model of third order, with an absolute value function as the output nonlinearity. This data set is quite challenging due to its small size, the relatively poor damping of the process, and the strong nonlinear effect. The system that generated the second set of data consists of two cascaded tanks with free outlets. It is well known that this laboratory process can be modeled with two coupled non-linear ordinary differential equations [16]. The third set of data is generated by an electronic nonlinear feedback laboratory system (denoted "the silver box") [11]. This system simulates a second order mechanical system, with a nonlinear spring constant. It can e.g. be thought of as a model of a nonlinear damper. To summarize, the three sets provide data useful for algorithms based on block oriented models [4], as well as for algorithms based on general nonlinear dynamic models of both discrete time type [2] and continuous time [16], [17] type.

The paper is organized as follows. Section 2 briefly discusses properties of benchmarking data sets. Section 3, 4 and 5 then describe the processes that were used for data generation. The recorded data sets are discussed in section 6. Previous identification results using the data sets are summarized in section 7. Conclusions follow in section 8.

II. Properties of Data for Nonlinear System Identification

In order for a set of reference data to be really useful for development of *nonlinear* system identification algorithms, a number of properties of the data set are desirable, although perhaps not necessary. Together, these properties should

Manuscript received October 16, 2012. This work is partially sponsored by the Fund for Scientific Research (FWO-Vlaanderen), the Flemish Government (Methusalem Grant METH-1), and the Belgian Program on Inter-university Poles of Attraction initiated by the Belgian State, Prime Minister's Office, Science Policy programming (IAP VI/4 - DYSCO).

Torbjörn Wigren is with the Division of Systems and Control, Department of Information Technology, Uppsala University, SE 75105 Uppsala, Sweden e-mail:torbjorn.wigren@it.uu.se.

Johan Schoukens is with the Department ELEC, Pleinlaan 2,Vrije Universiteit Brussel, B1050 Brussels, Belgium e-mail: johan.schoukens@vub.ac.be.

make it possible to compare results obtained during algorithm development to a reasonably well known true result without having to spend too much time on finding out how the system that generates the data behaves dynamically. The situation is hence a little different from the situation when system identification is applied to an unknown system.

A. Processes

A first desirable property is that the system that generates the data is sufficiently well defined structurally. This means that it is an advantage if it is possible to write down a dynamic model for the system, be it from physical laws, additional extensive system identification experiments, or by other considerations. In a typical case this model would be expressed as a set of nonlinear differential or difference equations, possibly together with static nonlinear transformations. It is advantageous if the effects of un-modeled dynamics and other disturbances are described too.

Secondly, the system dynamics should not be too complicated. A low order nonlinear system with one or a few pronounced nonlinear effects is preferred. This makes the data set accessible for algorithm developers without very time consuming and extensive studies of new technological areas. Furthermore, complicated high order systems are more likely to be subject to secondary algorithmic effects involving stiff systems of differential equations, ill-conditioning, observability issues, and other effects that are problem specific, and that do not represent the first priority during development of algorithms for nonlinear system identification. In other words, system identification using the data should not be so overwhelmingly difficult that it prevents development rather than supporting it.

Thirdly, systems of both continuous time and discrete time type should be made available as reference data. Discrete time systems have admittedly been at the focal point of linear system identification for a long time. However, in case of nonlinear systems in engineering applications, the connections to the underlying analogue mechanisms that govern the data generation are interesting as such [5]. Then system identification algorithms that recover parameters that can be easily related to these mechanisms become more interesting. Further reasons for the use of continuous time modeling appear in the next subsection.

B. Data

Obviously, the data generation and the measurements need to be well defined in order to allow different users to compare results. Turning the attention to the data generation itself, input signals that are suitable for nonlinear system identification need to be selected. Note that the PRBS is usually a poor choice. The reason is that also the amplitude contents and distribution of the signals are of central importance in nonlinear system identification [18]. In general, the excitation conditions on the input signals are much more complicated for nonlinear systems identification, than for linear system identification. In particular, the input signal levels and amplitudes need to be selected so that the nonlinear effects of the system come into play. This can mean that higher input signal amplitudes are preferred than what may be the choice for linear system identification where nonlinear effects rather need to be avoided. A consequence is that the signal to noise ratio may be higher than what may be preferred for benchmark data for linear algorithms. Due to the higher signal levels, also the effect of un-modeled dynamics can then be expected to be higher than in linear system identification. There are exceptions to this though. When non-linear friction is modeled it may e.g. be suitable to use very low signal levels. Finally, it is always important to remember that the superposition principle is not valid. Note in particular that removal of mean signal levels cannot be used as in linear system identification.

Another important fact is that there is in general no one-to-one sampling technique for nonlinear systems that allows a “loss-less” transformation between continuous time and discrete time models. This is very different from the linear case where zero-order hold sampling allows for this, provided that the sampling theorem is fulfilled [19]. For this reason it is often wise to use relatively fast sampling for non-linear systems, to avoid aliasing effects. A further reason for this is that the superposition principle cannot be assumed to hold, hence post-filtering of data cannot be applied in a straightforward manner any more [18]. The same is true for drifting disturbances, where de-trending becomes tricky and may have to be built into the identified model.

Other choices relate to the size of the recorded data set. There are reasons to believe that algorithms for identification of nonlinear systems may need longer data sets than identification algorithms for linear systems. One reason for this is that black box model structures for nonlinear systems are sometimes based on series expansions of nonlinearities, e.g. Volterra series expansions. The consequence is that the number of parameters grows very fast with the order of the system, resulting in an increased need for data to achieve a sufficient amount of data compression. This is however not necessarily true for block-oriented systems [15]. Therefore there is still a need also for shorter data sets that force developers to strive for algorithms that do not rely on huge sets of data. Perhaps it is safe to conclude that data sets for benchmarking and development of nonlinear systems should include both small sets of data, together with sets that allows for convergence of algorithms that choose to estimate larger number of parameters with more slow adaptation methods.

III. Coupled Electric Drives

A. Laboratory process and experimental setup

The CE8 coupled electric drives [14] consists of two electric motors that drive a pulley using a flexible belt. The system is depicted in Fig. 1. The pulley is held by a spring, resulting in a lightly damped dynamic mode. The electric drives can be individually controlled allowing the tension and the speed of the belt to be simultaneously controlled. The drive control is symmetric around zero, hence both clockwise and counter clockwise movement is possible. Here the focus is only on the speed control system. The reason is that the angular speed of the pulley is measured with a pulse counter and this sensor is *insensitive to the sign of the velocity*. Following the sensor, analogue low pass filtering and anti-aliasing filtering is applied. The dynamic effects are generated by the electric drive time constants, the spring and the analogue low pass filtering. The latter has a quite limited effect on the output and may be neglected.

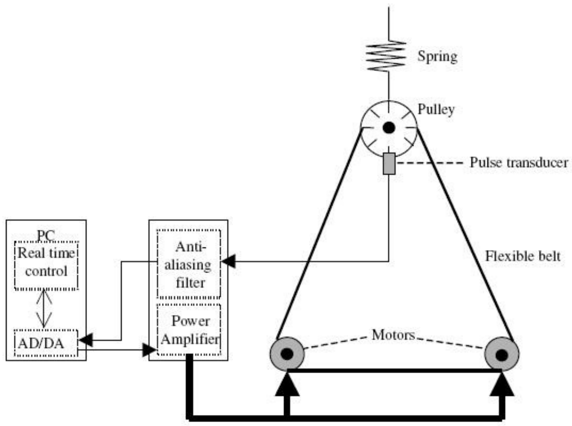

Fig. 1: The CE8 coupled electric drives.

B. Models

By considering the sum of the voltages applied to the motors as the input, physical modeling results in a lightly damped linear third order system, as measured from voltages to pulley velocity. The pulley velocity is rectified by the pulse counter to give the speed, after which it is filtered. A tentative first discrete time description of this system is

$$y(t) = \frac{b_1 q^{-1} + b_2 q^{-2} + b_3 q^{-3}}{1 + f_1 q^{-1} + f_2 q^{-2} + f_3 q^{-3}} u(t) + w(t) \tag{1}$$

$$y_n(t) = |y(t)| + e(t), \tag{2}$$

where $\{b_i\}_1^3, \{f_i\}_1^3$ are parameters, $u(t)$ is the input signal, $y_n(t)$ is the output signal, while $e(t)$ and $w(t)$ denote disturbances. The signal $y(t)$ is not available for measurement. The exact model of the analogue filtering is not known, however the bandwidth of the anti-aliasing filter is close to 12 Hz. This is less than the sensor bandwidth. Equations (1) – (2) clearly represents a Wiener model.

It could also be possible to attempt modeling including the anti-aliasing filter. A discrete time model for this case would be of Wiener – Hammerstein type and could be written as

$$y(t) = \frac{b_1 q^{-1} + b_2 q^{-2} + b_3 q^{-3}}{1 + f_1 q^{-1} + f_2 q^{-2} + f_3 q^{-3}} u(t) + w(t) \tag{3}$$

$$z(t) = |y(t)| + e(t), \tag{4}$$

$$y_n(t) = \frac{c_1 q^{-1} + \ldots + c_n q^{-n}}{1 + d_1 q^{-1} + \ldots + d_n q^{-n}} z(t) + v(t) \cdot \tag{5}$$

Here $y(t)$ and $z(t)$ are not available for measurement, and $v(t)$ denotes a third disturbance. Modeling using the approach of (3) – (5) remains to be attempted.

IV. CASCADED TANKS

A. Laboratory process and experimental setup

The second process is a fluid level control system consisting of two cascaded tanks with free outlets fed by a pump. The water is transported by the pump to the upper of the two tanks. The process is depicted in Fig. 2. The input signal to the process is the voltage applied to the pump and the two output signals consist of measurements of the water levels of the tanks. Since the outlets are open, and since the tanks are deep with large vertical extension, the result is a significantly non-linear dynamics that varies with the level of water. The process is controlled from a PC equipped with MATLAB interfaces to A/D and D/A converters attached to the water level sensors and the actuator pump. The sensors are linear with a much higher bandwidth than the process. They produce very little noise.

B. Models

The laboratory process is suitable for physical modeling. Application of Bernoulli's principle and conservation of mass results in

$$\begin{pmatrix} \dfrac{dh_1}{dt} \\ \dfrac{dh_2}{dt} \end{pmatrix} = \begin{pmatrix} -\dfrac{a_1\sqrt{2g}}{A_1}\sqrt{h_1} + \dfrac{1}{A_1} k u(t) \\ -\dfrac{a_2\sqrt{2g}}{A_2}\sqrt{h_2} + \dfrac{a_1\sqrt{2g}}{A_2}\sqrt{h_1} \end{pmatrix} . \tag{6}$$

Here h_1 and h_2 denote the levels of the upper and the lower tank, respectively. The areas of the tanks are A_1 and A_2 while the effluent areas are denoted a_1 and a_2. The gravity is denoted by g, the voltage to input flow conversion constant by k and the applied voltage to the pump by $u(t)$. Introducing the output signals $y_1(t)$ and $y_2(t)$ for the upper and lower tank, and adding system and output disturbances, results in the state space model

$$\begin{pmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{pmatrix} = \begin{pmatrix} -k_1\sqrt{x_1(t)} \\ k_2\sqrt{x_1(t)} - k_3\sqrt{x_2(t)} \end{pmatrix} + \begin{pmatrix} k_4 u(t) \\ 0 \end{pmatrix} + \begin{pmatrix} w_1(t) \\ w_2(t) \end{pmatrix} \tag{7}$$

$$\begin{pmatrix} y_1(t) \\ y_2(t) \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} x_1(t) \\ x_2(t) \end{pmatrix} + \begin{pmatrix} e_1(t) \\ e_2(t) \end{pmatrix}. \tag{8}$$

Here $x_1(t)$ and $x_2(t)$ are states, $w_1(t)$ and $w_2(t)$ are system disturbances while $e_1(t)$ and $e_2(t)$ describe measurement errors. k_1 - k_4 denote system parameters.

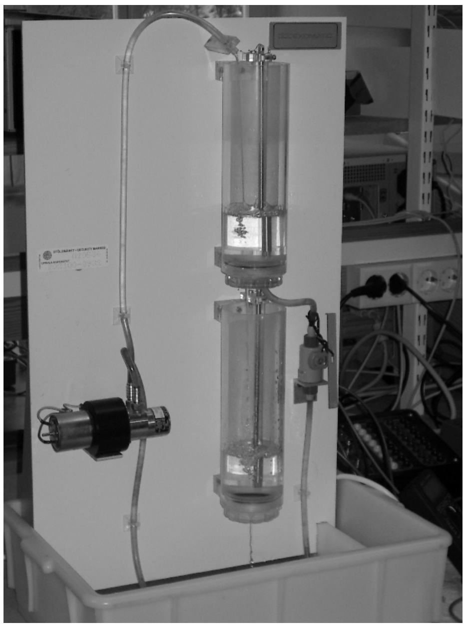

Fig. 2. The cascaded tank laboratory process.

Applying results of [16] shows that the dynamics of the level of the second tank can also be locally transformed to

$$\begin{pmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{pmatrix} = \begin{pmatrix} x_2(t) \\ f(x_1(t), x_2(t), u(t), \dot{u}(t), \theta) \end{pmatrix} \tag{9}$$

$$y_2(t) = x_1(t) + e_2(t), \tag{10}$$

where $x_1(t)$ and $x_2(t)$ are new states, θ is a parameter vector and where $f(,,,)$ is a scalar function.

V. Silver Box

A. Laboratory process and experimental setup

Mechanical oscillating processes constitute an important set of nonlinear dynamic systems. Examples include e.g. suspensions in motor vehicles, where shock absorbers and progressive springs are important components. The data generated by the silver box constitute a simple representation of such a combined component. The electrical circuit generating the data is close to but not exactly equal to the idealized representations described below.

The system was excited with a general waveform generator (HPE1445A). The generation of the input starts from a discrete time signal $r(k)$ that is transferred into an analogue signal $r_c(t)$ using a zero-order-hold reconstruction. The actual excitation signal $u_0(t)$ is then obtained by passing this signal through an analogue low-pass filter $G(p)$ in order to eliminate the high frequency contents around the multiples of the sampling frequency. Here p denotes the differentiation operator. The input is therefore given by

$$u_o(t) = G(p) r_c(t). \tag{11}$$

The input and the output signals were measured using a HP1430A data acquisition cards. The clocks of the acquisition and generator cards were synchronized. The sampling frequency was

$$f_s = \frac{10^7}{2^{14}} = 610.35 \quad Hz. \tag{12}$$

B. Models

The silver box uses analogue electrical circuitry to generate measured data representing a nonlinear mechanical resonating system with a moving mass m, a viscous damping d, and a nonlinear spring $k(y)$. The electrical circuit is designed to relate the displacement $y(t)$ (the output) to the force $u(t)$ (the input) by the following differential equation

$$m \frac{d^2 y(t)}{dt} + d \frac{dy(t)}{dt} + k(y(t)) y(t) = u(t) \tag{13}$$

The nonlinear progressive spring is described by a static but position-dependent stiffness

$$k(y(t)) = a + b y^2(t) \tag{14}$$

The signal to noise ratio is high enough to warrant modeling without a measurement noise. However, measurement noise can easily be added by replacement of $y(t)$ with the artificial variable $x(t)$ in (13), and by introduction of the disturbances $w(t)$ and $e(t)$ as

$$m \frac{d^2 x(t)}{dt} + d \frac{dx(t)}{dt} + k(x(t)) x(t) = u(t) + w(t) \tag{15}$$

$$k(x(t)) = a + b x^2(t) \tag{16}$$

$$y(t) = x(t) + e(t). \tag{17}$$

It can be noted that the silver box matches the model structure of [16] perfectly.

VI. Data Sets

A. Coupled electric drives

Two types of inputs were used for the coupled electric drives. The first input signal was a PRBS with a clock period of 5 times the sampling period. The signal was switching between $-u_{PRBS}$ V and $+u_{PRBS}$ V, resulting in the process changing the belt rotation direction frequently. Three open loop realizations were recorded for $u_{PRBS} = 0.5, 1.0, 1.5$. The input-output data was collected with a sampling period of 20 ms. Note that the 50 Hz sampling frequency is significantly higher than the bandwidth of the anti-aliasing filter. This should make some modeling of this filter possible, following (3)-(5). The second type of input signal was obtained from a PRBS with a clock period of 5 times the sampling period, switching between -1.0 V. and +1.5 V (first realization), as well as between -1.0 V and +3.0V (second realization). The signal in each clock interval of constant signal level, and with a duration of 5 sampling periods, was then multiplied with a random number, uniformly distributed in amplitude between 0 and 1. The resulting input signal is then uniformly distributed in amplitude. The reason for this is that when the system is nonlinear, both the frequency and amplitude contents of the input signal are important for identification [18]. The input-output data was again recorded with a sampling period of 20 ms. The input-output data obtained from the second realization of the uniformly distributed input signal is depicted in Fig. 3. The data sets are available for free download, see [20].

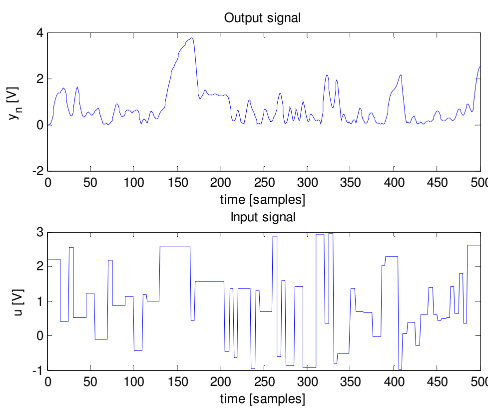

Fig. 3: Input-output data from the coupled electric drives speed system. Note the bias of the input.

B. Cascaded tanks

The data that was recorded from the cascaded tanks also used an input signal that was generated as the uniformly distributed input signal above. The first set of data for the process used a clock period of 30, a sampling period of 5.0 s and provide 2500 samples of input-output data for both the upper and lower tank. The second set of data was generated with a clock period of 15 samples, a sampling period of 4.0 s, and 7500 samples of data were recorded. The first set of data is illustrated in Fig. 4. The data sets are available for free download, see [20].

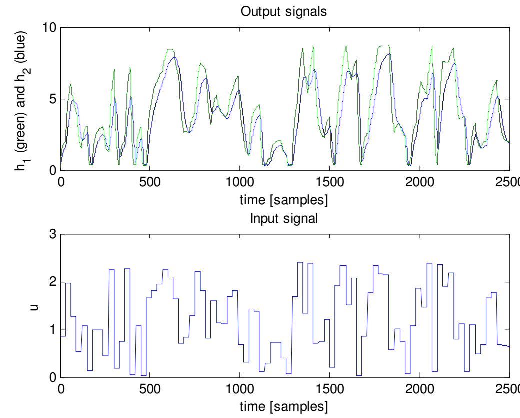

Fig. 4: Input-output data from the cascaded tanks.

C. Silver box

The reference signal $r(k)$ consists of two parts: The first part (40 000 samples) is a white Gaussian noise sequence filtered by a 9th order discrete time Butterworth filter with a cut-off frequency of 200 Hz. The amplitude is varied linearly over the interval from zero to its maximum value. The second part of the signal consists of 10 successive realizations of a random odd multi-sine signal given by

$$r(k) = A \sum_{\substack{l=1 \\ l \ \text{odd}}}^{l_{\max}} \cos(2\pi f_0 l + \varphi_l). \tag{18}$$

Only the odd harmonics are therefore excited. The amplitude A is scaled such that the signal fits well within the range of the generator. The period of the multi-sine is $1/f_0$, with $f_0 = f_s/8192\ s^{-1}$. The number of excited odd harmonics is 1342 ($f_{\max} \approx 200$ Hz). The phases φ_l are independent and uniformly distributed in $[0,2\pi[$. Ten realizations of the random odd multi-sine were merged, each of them separated by 100 zeros to indicate the start of a new realization. The data generated by the system is shown in Fig. 5. and Fig. 6. More information on the silver box data can be found in [11]. The data set is available for free download, see [21].

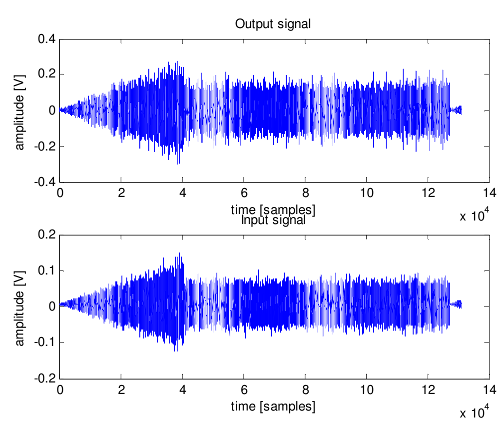

Fig. 5: input-output data from the silver box.

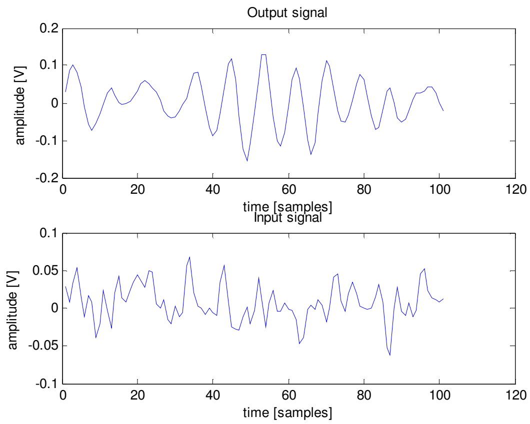

Fig. 6: input-output data from the silver box, expanded time example.

VII. Previous Identification Results

The coupled electrical drives process was identified using a recursive prediction error method based on the nonlinear Wiener model in [15]. The cascaded tank process was recursively identified with a prediction error method, based on a general state space model in [16]. The Kalman filter based initialization scheme of [17] was applied to this data set as well. It is expected that these results can be improved since they are based on recursive algorithms. The possibility to model the coupled electric drives with a Wiener Hammerstein model has not yet been explored. The silver box data has been used by [22]-[28].

VIII. Conclusion

This paper has presented three freely downloadable sets of data, suitable for support of the development, characterization and benchmarking of new nonlinear system identification algorithms. The intention is to support future work in the field. The properties of data sets suitable for such development were also discussed.

References

[1] The Mathworks, *MATLAB System Identification Toolbox*. 2012. *Available:* http://www.mathworks.com/products/sysid/

[2] L. Ljung, "Non-linear black box models in system identification", *Proc. IFAC Symposium on Advanced Control of Chemical Processes, ADCHEM'97,* Banff, Canada, pp. 1-13, 1997.

[3] J. Sjöberg and L. Ljung, "Overtraining, regularization, and searching for minimum in neural networks" *Proc. Symp. On Adaptive systems in Control and Signal Processing.* Grenoble, Switzerland. 1992.

[4] S. A. Billings and S. Y. Fakhouri, "Identification of systems containing linear dynamic and static nonlinear elements", *Automatica*, vol. 18, pp. no. 1, 15-26, 1982.

[5] T. Bohlin, "A case study of grey box identification", *Automatica*, vol. 30, pp. 307-318, 1994.

[6] J. C. Gomez, A. Jutan and E. Baeyens, "Wiener model identification and predictive control of a pH neutralization process", *IEE Proceedings of Control Theory and Applications",* vol. 151, no. 3, pp. 329-338, 2004.

[7] L. Brus and D. Zambrano, "Black-box identification of solar collector dynamics with variant time delay", *Control Eng. Practice*, vol. 18, no. 10, pp. 1133-1146, 2010.

[8] M. M. Silva, "Prediction error identification of minimally parameterized Wiener models in anesthesia", *in Proc. 18th IFAC World Congress*, pp. 5615-5620, Milan, Italy, 2011.

[9] J. M. A. Tanskanen, A. Huang and I. O. Hartimo, "Predictive power estimators in CDMA closed loop power control", *in Proc. IEEE VTC 98,* Ottawa, Ont. Canada, vol. 2, pp. 1091-1095, 1998.

[10] L. Ljung, *System Identification – Theory For The User.* 2nd Ed., *Prentice Hall, Upper Saddle River, N.J., 1999.*

[11] R. Pintelon and J. Schoukens. *System Identification - A Frequency Domain Approach*. IEEE Press, 2001.

[12] J. Schoukens, J. Suykens, and L. Ljung, "Wiener-Hammerstein benchmark", In 15th IFAC Symposium on System Identification (SYSID 2009), St. Malo, France, July 6-8, 2009.

[13] B. L. R. De Moor (ed.), "DaISy: database for the identification of systems", Dep. Electrical. Eng., K.U.Leuven, Belgium, 2012.

[14] P. E. Wellstead, *Introduction to Physical System Modeling*. Academic Press, London, UK, 1979.

[15] T. Wigren, Recursive identification based on the nonlinear Wiener model. Ph.D thesis, Acta Universitatis Upsaliensis, Uppsala Dissertations from the Faculty of Science 31, Uppsala University, Uppsala, Sweden, 1990. Available: http://user.it.uu.se/~tw/

[16] T. Wigren, "Recursive prediction error identification and scaling of non-linear state space models using a restricted black-box parameterization", *Automatica*, vol. 42, pp. 159-168, 2006.

[17] L. Brus, T. Wigren and B. Carlsson, "Initialization of a nonlinear identification algorithm applied to laboratory plant data", *IEEE Trans. Contr. Sys. Tech*., vol. 16, no. 4, pp. 708-716, 2008.

[18] T. Wigren, "User choices and model validation in system identification using nonlinear Wiener models", *Prep. 13:th IFAC Symposium on System Identification*, Rotterdam, The Netherlands, pp. 863-868, August 27-29, 2003. Invited session.

[19] K. J. Åström and B. Wittenmark, *Computer Controlled Systems,* Englewood Cliffs, NJ: Prentice Hall, 1984.

[20] T. Wigren, "Input-output data sets for development and benchmarking in nonlinear identification", Technical Reports from the department of Information Technology 2010-020, Uppsala University, Uppsala, Sweden, August, 2010. Available: http://www.it.uu.se/research/publications/reports/2010-020/NonlinearData.zip,

[21] T. Wigren and J. Schoukens, "Data for benchmarking in nonlinear system identification", Technical Reports from the department of Information Technology 2013-006, Uppsala, Sweden, March 2013. Avaliable: http://www.it.uu.se/research/publications/reports/2013-006/SNLA80mVZipped.zip

[22] L. Ljung, Q. Zhang, P. Lindskog, and A. Juditski, "Modeling a non-linear electric circuit with black box and grey box models", *Proc. IFAC Symposium on Nonlinear Control Systems (NOLCOS2004)*, pp. 543-548, 2004.

[23] V. Verdult, "Identication of local linear state-space models: the silver-box case study*", Proc. IFAC Symposium on Nonlinear Control Systems (NOLCOS2004),* pp. 537-542, 2004.

[24] L. Sragner, J. Schoukens, and G. Horvath, "Modeling of slightly nonlinear systems: a neural network approach", *Proc. IFAC Symposium on Nonlinear Control Systems (NOLCOS2004),* pp. 531-536, 2004.

[25] M. Espinoza, K. Pelckmans, L. Hoegaerts, J. Suykens, and B. D. Moor, "A comparative study of ls-svms applied to the silver box identication problem", *Proc. IFAC Symposium on Nonlinear Control Systems (NOLCOS2004),* pp. 513-518, 2004.

[26] J. Paduart, G. Horvath, and J. Schoukens, "Fast identication of systems with nonlinear feedback", *Proc. IFAC Symposium on Non-linear Control Systems (NOLCOS2004),* pp. 525-530, 2004.

[27] H. Hjalmarsson and J. Schoukens, "On direct identication of physical parameters in nonlinear models", *Proc. IFAC Symposium on Nonlinear Control Systems (NOLCOS2004),* pp. 519-524, 2004.

[28] J. Paduart, L. Lauwers, J. Swevers, K. Smolders, J. Schoukens, and R. Pintelon, "Identication of nonlinear systems using Polynomial Nonlinear State Space models", *Automatica,* vol. 46, no. 4, pp. 647-656, 2010.