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Benchmarks for Identification[1]

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Abstract

This report describes the preliminary steps for setting up a benchmark collection for identification. The identification protocol is described, where aspects as experiment set-up, signal pre-processing, modelling, parametrization, estimation methods and model validation are reviewed briefly. The relation of identification and control is stipulated. An analysis is given of requirements for good benchmarks for identification and some relevant organisational issues are addressed.

1. Introduction

In their paper, De Moor et al. (1997) point out that there is a need for a publicly available standard collection of test data that can be used in the field of data analysis, system identification and signal processing. They argue that such a collection could contribute to *the reproducibility of results* obtained by applying an identification method. (We will restrict ourselves in this report mainly to identification of systems.) Indeed, a really vast amount of identification methods, often with implementations on practical examples from all kinds of application fields, has been presented in the last four decades. Nevertheless (or maybe because of this) it is not clear at all at this moment how well all these methods perform when they are used in the great variety of practical situations.

If we would like to clarify the issue of performance of identification methods in practical applications, we should expand this idea of a standard collection of test data to that of a standard collection of benchmarks for identification. Benchmarking is a commonly accepted activity in many domains of today's science and technical activities, see e.g. the site http://www.esat.kuleuven.ac.be/sista/daisy/links.html which lists many websites with benchmark data in various fields.

A benchmark collection for identification can be valuable:

- *to measure the performance of methods and their related algorithms in the various (difficult) circumstances of applications*
- *to show the state-of-the-art of the identification field (for the method, the related algorithm and the implemented software code)*
- *to reveal the capabilities and limits of the methods*
- *to make comparisons of methods and their related algorithms straightforward*
- *to stimulate collaboration and interaction between researchers*
- *to compare the cost versus the effectiveness of methods*
- *to point to real life problems in practical applications that are still unresolved*
- *to evoke inspiration for developing identification methods that are tailored to industrial and/or practical needs*
- *to be used as a didactical tool*

Looking at the really vast literature on identification, it is remarkable that only a few attempts have been made to compare identification methods and results based on benchmark processes:

- *the so-called Åström process*
  This is a simulated linear SISO second-order process, introduced by Åström in the sixties. It has served since as the key example process for testing identification methods.
- *the test example of the IFAC 1973 Identification Symposium*
  This test example, see Isermann (1973a and 1973b) and Isermann et al. (1973), consists of three linear SISO processes: the Åström process, a second-order non-minimum phase process and a third-order low pass delay process. The output of all these processes is corrupted by noise which is shaped by a second-order low pass filter.
- *the DAISY collection of test data (1997)*

The Database for Identification of Systems (DAISY) was introduced by De Moor et al. (1977). They created a publicly accessible website (http://www.esat.kuleuven.ac.be/sista/daisy), to which authors can submit datasets. Some of these datasets may evolve into real benchmarks, which will facilitate a comparison of the performance of algorithms; see Appendices A and B.

Before discussing benchmarks for identification in more detail, it is worthwhile to look at the benchmark activities in control engineering, because of the strong interaction between identification and control.

Benchmarks for robust and adaptive control

1. *The ACC 90/91/92 benchmark and the ASCC 94 benchmark.*
   i) The ACC benchmark, see Wie et al. (1992), is a two-mass/spring system, which is a generic model of an uncertain dynamical system with uncolocated sensor and actuator. There are four control design problems formulated where the designer has the opportunity to consider additional design trade-offs for a realistic control design, by including the effects of unmodeled high frequency dynamics, actuator/sensor dynamics, bandwith limit, time delay etc. Several designs have been presented by various authors.
   ii) The ASCC benchmark, see Hara et al. (1994), is a model of a three-mass system. There are three position control problems and three velocity control problems (for each two basic and one advanced). Several designs have been presented.
2. *The IFAC'93 (or Sydney) benchmark* (Graebe, 1994) offers a problem statement with a time-varying single-input single-output test process in closed loop with a user defined controller, which has to be controlled for three different levels of time variance (stress levels). In this benchmark example, the process structure was unknown to investigators and the process is only accessible via a computer simulation. This was done intentionally, as a-priori knowledge of the plant to be controlled imprints a severe bias on the results. Knowledge of e.g. noise covariances, model structure and parameter variations influence the choice of filters, forgetting factors and other design parameters. The true process was published afterwards; it was seventh order and contained a varying non-minimum phase zero, varying time constants, high frequent resonant poles which were fixed, and varying low frequent resonant poles. Nine different solutions to the benchmark assignment have been reported which span a wide range of approaches such as adaptive (predictive) control, model reference adaptive control, robust pole placement, adaptive PI control, adaptive control with supervision, partial state model reference control, H_∞ robust control, and robust stability degree assignment. Graebe states that "a comparison of the results has highlighted the interplay between various modern and classical adaptive and robust design strategies, and revealed trade-offs between controller complexity, estimator complexity, supervision and performance".

Benchmarks for Computer Aided Control Systems Design (CACSD). The Benchmark Working Group of the IEEE Technical Committee on CACSD has published several benchmark problems in order to evaluate the capabilities of CACSD software with respect to performance and accuracy: a Grumman F-14 aircraft (CACSD benchmark 1), a continuous-time missile autopilot (CACSD benchmark 2), (for both benchmarks see Frederick, 1988), two linear hybrid multirate systems (CACSD benchmark 3), see Huang et al. (1992).

Benchmarks in process-industry:
Shell benchmark; see Shell workshop, see Prett et al. (1987). This benchmark deals with a simulation of a heavy oil fractionator, where the process model (first order deadtime) and uncertainties in the gains of the model are given. The control objectives and control constraints as well as five prototype test cases are specified.
Distillation column model, see Skogestadt et al. (1996) and also the site http://www.kkt.chembio.ntnu.no/research/Process_Control/). This simulation of a distillation column can very well be used as a benchmark for process identification. It is implemented in Matlab/Simulink and enables testing for identification. The simulator quite well reflects main mechanisms of a distillation process, which include multivariable system characteristics, directionality and stiff system behaviour.

First principles based process simulators may very well serve as good benchmarks for testing various identification and parameter estimation techniques. The increasing power of the internet and of the computer systems connected to it may be applied for developing applications for benchmarking that can be used for *webcomputing*. This allows testing against a given fixed simulated process with specific characteristics. The conditions applicable during testing are in this case equivalent for all tests applied, which makes objective comparison between the results obtained with different techniques easier and more reliable.

2. Identification of processes

The goal of this paper is to establish rules for benchmarks for identification. Therefore we will analyse those aspects of the identification procedure, which are relevant for setting up such benchmarks.

The identification protocol consists of three successive phases, as introduced by Ljung (1987), prepar*ation*, *estimation* and *validation*. An outer loop is part of the protocol, enabling a re-iteration in the phases if the validation phase rejects the obtained model. The identification procedure is typically an iterative one, where insights and judgements of the user are mingled with formal calculations, extensive data handling and computer algorithms. A wealth of good textbooks is available: Eykhoff (1974), Söderström et al. (1989), Ljung (1987, 1995), Zhu et al. (1993).

2.1. Preparation phase

The first phase in the identification protocol is the **preparation phase**. The goal of this phase is to produce a reliable dataset as input for the estimation phase. Here we have steps that are indispensable in every identification task: definition of the intended use of the model, experi-ment design and signal pre-processing; see Backx et al. (1989a, 1989b). Depending on the actual approach chosen in subsequent phases of the identification protocol, this preparation phase usually includes in the given order:

i) concise formulation of the intended use of the model. A model is justified solely by its intended use. The intended use fully determines the type of model, its extensiveness and necessary precision needed. Often a linear model is sought for the operation of a process working about a specific working point. The intended use of a model can be understanding and explanation of the behaviour of the process; then 'white' models - which are based on physical laws etc.- are appropriate. If the model is meant for controller design, a 'black box' model -which gives an input-output description of the dynamic behaviour- is a good choice.

ii) recovery of a-priori information from already available physical modelling, from insight in and experience with the process, and by interview of process operators.

iii) tests for stationarity and linearity (around a certain working point) using e.g. staircase signals.

iv) design of primary experiments with test signals leading to estimates of general, overall system characteristics, such as the largest and smallest system time constants (which determine the choices of the sampling interval and minimal required datalength), the noise characteristics and the system bandwidth (for design of noise rejection filter).

v) main experiments with pseudo random binary noise sequences (PRBNS) or other well-selected test signals leading to input and output signals which contain enough information for the estimation of the parameters of the dynamic model in the estimation phase.

vi) determination and compensation of delays.

vii) data pre-processing of signals obtained from step v): such as scaling, peak shaving for removal of outliers (spikes), removal of mean value and (seasonal) trends, correction of missing or damaged datapoints, and sample rate reduction.

2.2. Estimation phase

The second phase of the identification protocol is the **model estimation phase**, which is the extraction of a mathematical model from the set of pre-processed input-output data. Here the essential topics are:

- the *choice of the model set*,
- the *structure selection* for the this model set,
- the *choice of the identification criterion*
- the resulting *estimation method*

Three main approaches for ***the choice of model set*** will be mentioned:

i) non-parametric models. A general model with minimal or no structural information is sought; e.g. an impulse response or a FIR model. As a consequence of the poor structure of the model, the "parametrisation" of this kind of model sets leads to a large number of parameters. Such a model is in particular useful when little a-priori information on the process is available, and is also suited for a first iteration of an identification procedure leading to parametric models. Then, in subsequent iterations, a transformation to a more compact parametrised model is performed, often followed by model reduction.

ii) parametric models. A compact parametric model, with a minimal or limited number of parameters, such as e.g. (canonical) state space models, (canonical) matrix fraction description (MFD) models, and ARX-models.

iii) subspace models. The models in this approach are characterized by subspaces of spaces constructed from input-output data, and a state space model is estimated from these subspaces.

The following issues, related to choice of model sets, should be addressed:

- the *uniqueness* of the model set, i.e. each member of the model set represents a model with different dynamics. The minimization method for finding the best member of the set, i.e. that best fulfils the identification criterion, will otherwise run into problems.
- the *generality* of the set, i.e. the model set should be rich enough to represent the dynamics of the class of processes under study.
- the *numerical conditioning* of the parametrisation of the model set. Many standard input-output model structures seem to be sensitive to numerical errors.

If the model set is chosen, then some integer indices, representing the structure and order within the model set should be determined. Examples are the orders of the polynomials of an ARX model, or the integers that determine the structure of the [A,B,C,D] matrices of a certain canonical state space representation. This is the ***structure selection*** problem, which can be a tough task, especially in a multi-input multi-output case. The user should exploit available a-priori information and insight into the physical properties of the process. Structure and order tests are available which are based on correlation analysis of input-output data, or on rank determination of signal matrices. If little a-priori knowledge is available, then a good policy is to start with models with little structural properties, as e.g. FIR, like in the MPSSM approach, see hereafter.

The ***choice of the criterion*** is fully dominated by the intended use of the model. The models that are found as a result of the minimization of the criterion function should be seen as vehicles for achieving the object of the criterion: usually prediction or simulation. A one-step-ahead-prediction model will naturally put more emphasis on the high frequency band of the input-output dynamics, in order to produce a good prediction of the next output sample. Prediction models will usually perform well in a prediction type of application. However, if the model is used for controller design, the lower frequency band cannot be discarded. This strongly suggests the use of output error models or frequency weighted prediction error models for such applications.

Estimation methods:

A widely used method is the *prediction-error method* (PEM), which consists of:
- formulation of a prediction error for a chosen model structure,
- minimisation of an error criterion with respect to the model parameters.

As the PEM is a general method, it can successfully be used in connection with a great variety of model classes; see Ljung (1987).

Another approach is the *MPSSM method*, where the use of a MPSSM (minimal polynomial start sequence Markov parameters) model is essential. This model is based on the property that the Markov parameters larger than a certain value r of a finite impulse response (FIR) can be described as a linear combination (called the minimal polynomial) of previous Markov parameters. A detailed outline of the method is given in Backx et al. (1989a and 1989b). The estimation of a MPSSM model for MIMO processes consists of the following steps:

i) estimation of a high order FIR model using a PEM or output error method,
ii) determination of the degree r of the minimal polynomial from the estimated Markov parameters. Note that information on the structure is gained from the estimated FIR parameters.

iii) estimation of the parameters of an initial MPSSM model from the FIR model.
iv) adjustment of this MPSSM model to the original dataset.
v) model reduction to eliminate irrelevant dynamics in the model.

The most attractive features of the MPSSM method are:
i) the method has proven to be well suited for modelling MIMO processes.
ii) no a-priori structural information is needed. This is an important feature, in particular for MIMO and especially for practical applications, as cumbersome structural tests can be avoided.
iii) as a FIR model is a general parametrisation, the method is suited for modelling a large class of processes.
iv) the method is robust against local minima due to several precautions.

The term *Subspace Model Identification* (SMI) is used to indicate a number of related approaches that allow identifying state space models from input-output data in a non-iterative manner. The main property that characterizes these SMI schemes is the calculation of a *subspace* of spaces defined from the available input-output data records. Examples of such subspaces are the extended observability matrix, or the state vector sequences. SMI is suited for large order multivariable systems, delivering directly reduced order state space models without the need of canonical parametrisations, which cause usually numerically unreliable results for such processes. These properties of SMI are attractive and in fact compensate for the shortcomings of PEM. Therefore the SMI is seen as a promising development in identification. There are many research activities at this moment on SMI schemes; for a review see Viberg (1994).

Besides the subspace identification techniques also *orthonormal basis functions* based process identification have been developed in the past decade as a new, very promising technique for accurate modelling of relevant process dynamics (e.g. Heuberger et al., 1995). This technique is based on the use of a set of orthonormal functions that are used to reconstruct the impulse responses or step responses of the process. The model parameters are the weights that give the contribution of a specific basis function to the overall process dynamics. The applied basis functions can be infinite length basis functions or finite length basis functions. If the basis functions are chosen in line with the relevant process dynamics only a very few basis functions are needed for reconstructing the relevant process dynamics. This results in compact models that can describe complex process dynamics with just a very few parameters to be estimated. The methodology is also very well suited to integrate a-priori knowledge on relevant process dynamics by using this knowledge in the selection of basis functions. This way efficient, high performance process identification becomes feasible.

The *asymptotic method* (ASYM) of identification was developed for model-based controls such as linear robust control and Model Predictive Control; see Zhu et al. (1993) and Zhu (1998). The method makes extensive use of Ljung's asymptotic theory; see Ljung (1985) and Zhu (1989). The theory gives a simple expression for the model errors for high order models. The four problems, test signal design for control, model order/structure selection, parameter estimation and model validation, are solved in a systematic manner:
1. the spectra of test signals can be optimized for use in control. This can be done for both open loop and closed-loop tests.

2. model order is determined by equalizing the bias error and variance error in the frequency domain.
3. in parameter estimation, first a high order ARX model is estimated, and then a frequency domain maximum likelihood model reduction is performed.
4. upper error bounds of model frequency responses are estimated and used for model validation. If the model is invalidated, test redesign can be done easily using the error bound formulas.

The *frequency domain method* estimates the transfer function with time delay using periodic excitation signals. The measured signals are transformed to the frequency domain and a maximum likelihood estimator is used to find the coefficients of the transfer function. This leads to a nonlinear least squares problem. For a survey see Pintelon et al. (1994).

A very interesting comparison of estimation methods has been carried out by Zhu et al. (1994) on three of the above mentioned methods: PEM, SMI and ASYM. The authors fix their goal to identification for Model Predictive Control (MPC) and formulate the following evaluation criteria:
- *model accuracy*, defined as the simulation and prediction accuracy for the validation data set
- *speed* (computing time) *and robustness* (w.r.t. round-off errors, local minima, convergence problems) in model estimation
- *model order/structure selection* (complexity of test, robustness against undermodelling and disturbances, possibility of automation of test, MIMO versus MISO model structure)
- *model uncertainty description*
- *ability to find optimal input design for control*
- *possibility of closed loop identification*, what about *unstable processes*
- is *recursive estimation provided* (for adaptive control)

The three methods are used for identification of two industrial processes: a glass tube drawing process and a four effect (stage) evaporator. Their evaluation of the three methods, based on the test data, yields a detailed insight into the usefulness and the capabilities of these methods.

2.3. Validation phase

The final phase of the identification protocol is the **validation phase**. As in the preparation phase, there are approach independent tests such as cross model validation, and approach dependent tests such as residual whiteness tests, cross correlation tests and the extraction of statistical information about the estimates. We comment on these tests:
Cross model validation. The input-output data set is split into two parts: one part for estimation and the other part for validation. The performance of the estimated model parameters (with respect to prediction error or output error, measured outputs versus simulated outputs, etc.) when applied to the validation dataset is compared to that of the estimation dataset. Substantial differences yield an indication that the obtained model is strongly data-dependent and that the results have not converged. This is an appealing and powerful validation method. Weird, suspected parts in the dataset become apparent. A flexible simulation tool supported with powerful, user-friendly graphics is necessary for this test.
Face validation. This is a straightforward test where the process output and the model output are (graphically) compared. Too large deviations indicate that the model is of low quality.

Residual whiteness test. Coloured residuals (e.g. prediction errors) indicate that more information of process- or noise dynamics than explained by the linear model is present in the data set. In particular the structure of the noise model might be insufficient. Whiteness tests are appropriate for detecting this.
Cross-covariance between residuals and inputs. A correlation between past inputs and residuals is an indication that there is more dynamics in the process than has been incorporated in the linear model or that the data was collected during closed-loop operation. Calculation of the cross-covariance between input and residual with the appropriate confidence interval for given N can reveal this.
Akaike's Information Criterion (AIC). Akaike has proposed a refined criterion for selecting the order of the model, based on the behaviour of the identification criterion as function of the model order. A straightforward selection criterion for the model order based on the decrease of the identification criterion usually yields too high model orders, as this criterion is a continuously decreasing function of the model order.
Model reduction. Model reduction is useful for detecting whether the model found is of unnecessarily high order, due to e.g. near pole-zero cancellation pairs in the input-output transfer. ARX models in particular can show this behaviour, which can be explained as additional modelling of the noise dynamics as an excessive part of the modelling of the process dynamics. Standard model reduction schemes, which are part of a good control library, can be used.
Statistical properties of the estimates. To judge the value of the obtained model parameters or subspaces the knowledge of the uncertainty of these quantities is necessary. Estimates of such uncertainty regions and graphically displaying are important.

3. Benchmarking for identification

Process identification techniques are widely applied in industry for modelling of process dynamics for a wide range of applications. The applications that process identification techniques are predominantly used for are:

- Model Predictive Control
  Model predictive control systems essentially apply two models for calculating the control actions. The first model usage is for predicting infinite horizon future process output behaviour on the basis of known (past) input signals. The second model application is for the calculation of the best future process input manipulations to optimally drive the process to desired operating conditions.
- Inferential prediction of non-measurable variables
  Inferential prediction of non-measurable variables involves the estimation of a value of some process variables on the basis of the known history of process input signals and related variables. The purpose is obtaining the best estimate of the current value of the unknown signal using all information available of these known signals.
- Analysis of process dynamics for engineering purposes
  The analysis of process dynamics for engineering purposes implies obtaining detailed knowledge of specific process transfer characteristics like (damped) oscillatory behaviour, non-minimum phase behaviour, directionality and stiffness

of the transfer characteristics, differences in bandwidth between disturbance transfers and process transfers, …

- Process simulation
  Model usage for process simulation may imply different requirements on the models. Process simulation for training for example requires models that can accurately predict current process output signals on the basis of the past behaviour of inputs and disturbances. Simulation for optimization of future process output behaviour on the contrary requires models that give a best prediction of the infinite horizon future output behaviour.
- Plant wide process optimisation
  Plant wide optimization requires process models that can predict complete future process output behaviour on the basis of all currently known signal histories to optimize some given cost function (e.g. profit over complete future horizon).

Depending upon the application, requirements imposed on the model vary. Many applications do not require the model to be a very accurate representation of the process over a very broad operating range. Model inaccuracies are acceptable as long as they do not violate the performance of the application of the model. In general models need to be accurate at certain operating conditions or along specific trajectories. Also the accuracy requirements on the represented frequency characteristics depend on the application of the model. This also implies that *validation of the model has to be done in line with the application of the model*.

High performance model predictive control for example requires models that need to be accurate representations of the model dynamics in the frequency range that is at the cut-off frequency of the process. Furthermore the model needs to be accurate at frequencies where the dominant part of the disturbance affect process behaviour.
Process simulators used for operator training in general require models that on the average show dynamic behaviour, which roughly resembles actual process behaviour. Often it is not necessary to very accurately represent truly observed process dynamics. Especially steady state behaviour and non-linearities need to be covered well for these types of applications.
Inferential predictors need to give reliable estimates for inferred properties. Depending upon the use of these estimates additional requirements will be imposed. Frequently inferential predictors can be applied as fixed horizon or so-called n-step ahead predictors.

In general various validation criteria need to be developed to judge the model properties for its use. The model applied for prediction in the model predictive controller can best be validated using a Hankel norm type criterion, whereas the model applied for calculation of future control actions can often best be judged on the basis of an output error type criterion. The best criterion for validation of the model for control depends on the specific controller design specifications. Often it is also valuable to have information on the model inaccuracies. This information can be used for finding appropriate tuning of the control system to give the right balance between robustness and performance, see Ninnes et al. (1995).

Comparison of model characteristics obtained with the various identification and parameter estimation methods needs to be done on the criteria appropriate for the application of these models. A table like the one below may do this job.

Benchmark A	Integral Quadratic Output Error	Integral Quadratic prediction error	Integral absolute output error	…
Method 1				
Method 2				
Method 3				

3.1. Rules for useful benchmarks

Categories of benchmarks:

- model to known model under given conditions (inputs, S/N ratio etc.): estimation part
- identification protocol applied to data of known model
- identification protocol applied to data of unknown model (e.g. with webcomputing)
- identification protocol applied for model based controller (e.g. with webcomputing)

Benchmark examples need to be selected to represent the difficulties encountered over the broad range of applications of models. Typical problems encountered in practice are related to:

- Stiffness of the process both as function of frequency as well as in terms of directionality
- Multiple operating conditions with different requirements such as high performance control in a specific operating point, transition control between different operating points or start-up/shutdown of processes
- Specific disturbance characteristics of processes
- First or higher order integral behaviour of processes.

Good benchmarks reflect difficulties encountered in real life processes well and enable detailed analysis of the characteristics and performance of the techniques tested. The benchmark has to reveal weaknesses and strengths of the tested techniques. The judgement made on tested techniques has to be representative of for the behaviour of these techniques in practical applications. The benchmark needs to support tests at extreme conditions that will be rarely entered into in practice.

Typical properties of a good benchmark are:

- Actual process difficulties are also covered by the benchmark
- Nasty process behaviour that causes modelling difficulties needs to be accessible for detailed analysis and needs to be documented
- The benchmark should be representative for actual though process behaviour
- Performance demonstrated on a benchmark should be accepted as a realistic demonstration of capabilities of the tools tested

4. Organisational issues

The organisational issues of the benchmark collection for identification are similar to those of the benchmarks in other chapters of SLICOT. These issues were already described, see Mehrmann et.al.(1998). We quote from this report:

"Each topic of the SLICOT benchmark library is covered by a benchmark routine. These routines are implemented and maintained by a responsible partner (RP) of the NICONET project. Duties of the RP are the following:

- The RP has to look for benchmark examples. Benchmark examples can be found in publications, in public data bases (e.g. DAISY), etc.
- The RP collects the detected examples and those examples submitted by contributors outside NICONET.
- The RP has to decide which of the collected benchmark examples will be included in the respective benchmark collection.
- The RP implements the benchmark collection in the form of a benchmark routine. Moreover, he/she provides a documentation of this routine.
- The RP updates the benchmark collection when new interesting test problems are found. He/she provides the routine with release numbers."

5. Conclusions

Starting from an analysis of the identification protocol, where issues as experiment set-up, signal pre-processing, modelling, parametrization, estimation methods and model validation are considered, validation criteria for benchmarks were obtained, which depend on the intended use of the identified model. Four categories of benchmarks were proposed: model to known model under given conditions, identification protocol applied to data of known model, identification protocol applied to data of unknown model (e.g. with webcomputing), and identification protocol applied for model based controller (e.g. with webcomputing). Rules for good benchmarks, that reflect difficulties encountered in real life processes, were given and some organisational issues were addressed.

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Y.C. Zhu: *"Black-box identification of MIMO transfer functions: asymptotic properties of prediction error models"*; Int. J. Adaptive Control and Signal Processing, vol. 3, pp. 357-373, 1989.

Y.C. Zhu and T. Backx: *"Identification of Multivariable Industrial Processes for Simulation, Diagnosis and Control"*; Springer Verlag, Berlin, 1993.

Y.C. Zhu, P. Van Overschee, B. De Moor and L. Ljung: *"Comparison of three classes of identification methods"*; Proc. IFAC SYSID'94, vol.1, pp.175-180, 1994.

Y.C. Zhu: *"Multivariable process identification for MPC: the asymptotic method and its applications"*; Journal of Process Control, vol. 8, no. 2, pp. 101-115, 1998.

Appendix A: Overview of the DAISY collection

DAISY consists of the following datasets:

Process Industry Systems

D001 Simulation of a ethane-ethylene distillation column (4 series of 90 samples; 5 inputs, 3 outputs)
D002 Glass furnace (1247 samples; 3 inputs, 6 outputs)
D003 120 MW power plant (200 samples; 5 inputs, 3 outputs)
D004 Industrial evaporator (6305 samples; 3 inputs, 3 outputs)
D005 Simulation data of a pH neutralization process in a stirring tank (2001 samples; 2 inputs, 1 output)
D006 Step response of a fractional distillation column (250 samples; 3 inputs, 2 outputs)
D007 Industrial dryer (867 samples; 3 inputs, 3 outputs)
D008 Liquid-saturated steam heat exchanger (4000 samples, 1 input 1 output)
D009 Test setup of an industrial winding process (2500 samples; 5 inputs. 2 outputs)
D010 Continuous stirred tank reactor (7500 samples; 1 input, 2 outputs)
D011 Model of a steam generator (9600 samples; 4 inputs, 4 outputs)

Mechanical Systems

D101 Ball-and-beam setup at SISTA (1000 samples; 1 input, 1 output)
D102 Laboratory setup acting like a hair dryer (1000 samples; 1 input, 1 output)
D103 CD-player arm (2048 samples; 1 input, 1 output)
D104 Wing flutter data (1024 samples; 1 input, 1 output)
D105 Flexible robot arm (1024 samples; 1 input, 1 output)
D106 Experiment on a Steel Subframe Flexible structure (8523 samples; 2 inputs, 28 outputs)

Biomedical Systems

D201 Cutaneous potential recordings of a pregnant woman (2500 samples; 8 outputs)
D202 Tongue displacement shapes occuring in the pronunciation of english vowels

Environmental Systems

D301 Simulation of the western basin of Lake Erie (57 samples; 5 inputs. 2 outputs)

Thermic Systems

D401 Heat flow density through a two layer wall (1680 samples; 2 inputs, 1 output)
D402 Heating system (801 samples; 1 input, 1 output)

Simulators

D501 Simulator of in-vivo MRS signals

Time Series

D601 One hour of internet traffic between Lawrence Berkeley Laboratory and the rest of the world (99999 samples; 1 output)

Appendix B: Datafiles of the DAISY collection

D001: Simulation of a ethane-ethylene distillation column (4 series of 90 samples; 5 inputs, 3 outputs) destill.dat file.

1. Contributed by:

Peter Van Overschee
K.U.Leuven - ESAT - SISTA
K. Mercierlaan 94, 3001 Heverlee, Belgium
Peter.Vanoverschee@esat.kuleuven.ac.be

2. Process/Description:

Data of a simulation (not real !) related to the identification of an ethane-ethylene destillationcolumn. The series consists of 4 series:

U_dest, Y_dest: without noise (original series)
U_dest_n10, Y_dest_n10: 10 percent additive white noise
U_dest_n20, Y_dest_n20: 20 percent additive white noise
U_dest_n30, Y_dest_n30: 30 percent additive white noise

3. Sampling time: 15 min.

4. Number of samples: 90

5. Inputs:

a. ratio between the reboiler duty and the feed flow
b. ratio between the reflux rate and the feed flow
c. ratio between the distillate and the feed flow
d. input ethane composition
e. top pressure

6. Outputs:

a. top ethane composition
b. bottom ethylene composition
c. top-bottom differential pressure.

7. References:

R.P. Guidorzi, M.P. Losito, T. Muratori: *"The range error test in the structural identification of linear multivariable systems"*; IEEE Trans. Aut. Control, Vol 27, pp. 1044-1054, Oct. 1982.

8. Known properties/peculiarities

9. Some MATLAB-code to retrieve the data

```
!gunzip destill.dat.Z
load destill.dat
U=destill(:,1:20);
Y=destill(:,21:32);
U_dest=U(:,1:5);
U_dest_n10=U(:,6:10);
U_dest_n20=U(:,11:15);
U_dest_n30=U(:,16:20);
Y_dest=Y(:,1:3);
Y_dest_n10=Y(:,4:6);
Y_dest_n20=Y(:,7:9);
Y_dest_n30=Y(:,10:12);
```

D002: Glass furnace (1247 samples; 3 inputs, 6 outputs)

1. Contributed by:

Peter Van Overschee
K.U.Leuven - ESAT - SISTA
K. Mercierlaan 94, 3001 Heverlee, Belgium
Peter.Vanoverschee@esat.kuleuven.ac.be

2. Process/Description:

Data of a glassfurnace (Philips)

3. Sampling time

4. Number of samples: 1247

5. Inputs:

a. heating input
b. cooling input
c. heating input

6. Outputs:

a. 6 outputs from temperature sensors in a cross section of the furnace

7. References:

P. Van Overschee, B. De Moor: *"N4SID : Subspace Algorithms for the Identification of Combined Deterministic-Stochastic Systems"*; Automatica, Special Issue on Statistical Signal Processing and Control, Vol. 30, No. 1, 1994, pp. 75-93

P. Van Overschee: *"Subspace identification : Theory, Implementation, Application"*; Ph.D. Thesis, K.U.Leuven, February 1995.

8. Known properties/peculiarities

9. Some MATLAB-code to retrieve the data

```
!gunzip glassfurnace.dat.Z
load glassfurnace.dat
T=glassfurnace(:,1);
U=glassfurnace(:,2:4);
Y=glassfurnace(:,5:10);
```

D003: 120 MW power plant (200 samples; 5 inputs, 3 outputs)

1. Contributed by:

Peter Van Overschee
K.U.Leuven - ESAT - SISTA
K. Mercierlaan 94, 3001 Heverlee, Belgium
Peter.Vanoverschee@esat.kuleuven.ac.be

2. Process/Description:

data of a power plant (Pont-sur-Sambre (France)) of 120 MW

3. Sampling time: 1228.8 sec

4. Number of samples: 200 samples

5. Inputs:

1. gas flow
2. turbine valves opening
3. super heater spray flow
4. gas dampers
5. air flow

6. Outputs:

1. steam pressure
2. main stem temperature
3. reheat steam temperature

7. References:

R.P. Guidorzi, P. Rossi: *"Identification of a power plant from normal operating records"*; Automatic control theory and applications, Canada, vol. 2, pp. 63-67, sept 1974.

M. Moonen, B. De Moor, L. Vandenberghe, J. Vandewalle: *"On- and off-line identification of linear state-space models"*; Intern. Journal of Control, vol. 49, Jan. 1989, pp. 219-232

8. Known properties/peculiarities

9. Some MATLAB-code to retrieve the data

```
!gunzip powerplant.dat.Z
load powerplant.dat
U=powerplant(:,1:5);
Y=powerplant(:,6:8);
Yr=powerplant(:,9:11);
```

D004: Industrial evaporator (6305 samples; 3 inputs, 3 outputs)

1. Contributed by:

W. Favoreel
KULeuven
Departement Electrotechniek ESAT/SISTA
Kardinaal Mercierlaan 94, B-3001 Leuven, Belgium

2. Process/Description:

A four-stage evaporator to reduce the water content of a product, for example milk

3. Sampling time:

4. Number of samples: 6305

5. Inputs:

u1: feed flow to the first evaporator stage
u2: vapor flow to the first evaporator stage
u3: cooling water flow

6. Outputs:

y1: dry matter content
y2: flow of the outcoming product
y3: temperature of the outcoming product

7. References:

Y. Zhu, P. Van Overschee, B. De Moor, L. Ljung: *"Comparison of three classes of identification methods"*; Proc. of SYSID '94, Vol. 1, 4-6 July, Copenhagen, Denmark, pp. 175-180, 1994.

8. Known properties:

column 1: input u1
column 2: input u2
column 3: input u3
column 4: output y1
column 5: output y2
column 6: output y3

D005: Simulation data of a pH neutralization process in a stirring tank (2001 samples; 2 inputs, 1 output)

1. Contributed by:

Jairo Espinosa
K.U.Leuven ESAT-SISTA
K.Mercierlaan 94, B3001 Heverlee, Belgium
Jairo.Espinosa@esat.kuleuven.ac.be

2. Process/description:

Simulation data of a pH neutralization process in a constant volume stirring tank.
Volume of the tank 1100 liters
Concentration of the acid solution (HAC) 0.0032 Mol/l
Concentration of the base solution (NaOH) 0,05 Mol/l

3. Sampling time: 10 sec

4. Number of samples: 2001

5. Inputs:

u1: acid solution flow in liters
u2: base solution flow in liters

6. Outputs:

y: pH of the solution in the tank

7. References:

T.J. Mc Avoy, E. Hsu and S. Lowenthal: *"Dynamics of pH in controlled stirred tank reactor"*; Ind. Eng. Chem. Process Des. Develop., vol. 11 (1972), pp. 71-78

8. Known properties:

Highly non-linear system.
column 1: time-steps
column 2: input u1
column 3: input u2
column 4: output y

D006: Step response of a fractional distillation column (250 samples; 3 inputs, 2 outputs)

1. Contributed by:

Jan Maciejowski
Cambridge University, Engineering Department
Trumpington Street, Cambridge, CB2 1PZ, England.
jmm@eng.cam.ac.uk

2. Process/Description:

step response of a fractional distillation column (Simulation data supplied by SAST Ltd)
Steps are applied to each input, one at a time.
Input (a) is a step of amplitude 1.0
Input (b) is a step of amplitude 1.0
Input (c) is a step of amplitude 1.0

3. Sampling time: 10 sec

4. Number of samples: 250 samples

5. Inputs:

a. input cooling temperature
b. reboiling temperature
c. pressure

6. Outputs:

a. top product flow rate
b. C4 concentration

7. References:

J.M. Maciejowski: *"Parameter estimation of multivariable systems using balanced realizations"*; in: Bittanti,S. (ed), Identification, Adaptation, and Learning, Springer (NATO ASI Series), 1996.

C.T. Chou, J.M. Maciejowski: *"System Identification Using Balanced Parametrizations"*; IEEE Trans. Aut. Control, vol. 42, no. 7, July 1997, pp. 956-974.

8. Known properties/peculiarities:

9. Some MATLAB-code to retrieve the data

```
!gunzip distill_col.dat.Z
load distill_col.dat
u1y1=distill_col(:,2);  % step on input 1, response on output 1
u1y2=distill_col(:,3);  % step on input 1, response on output 2
u2y1=distill_col(:,4);  % etc
u2y2=distill_col(:,5);
u3y1=distill_col(:,6);
u3y2=distill_col(:,7);
```

D007: Industrial dryer (867 samples; 3 inputs, 3 outputs)

1. Contributed by:

Jan Maciejowski
Cambridge University, Engineering Department
Trumpington Street, Cambridge, CB2 1PZ, England.
jmm@eng.cam.ac.uk

2. Process/Description:

Data from an industrial dryer (by Cambridge Control Ltd)

3. Sampling time: 10 sec

4. Number of samples: 867 samples

5. Inputs:

a. fuel flow rate
b. hot gas exhaust fan speed
c. rate of flow of raw material

6. Outputs:

a. dry bulb temperature
b. wet bulb temperature
c. moisture content of raw material

7. References:

J.M. Maciejowski: *"Parameter estimation of multivariable systems using balanced realizations"*; in: Bittanti, S. (ed), Identification, Adaptation, and Learning, Springer (NATO ASI Series), 1996.

C.T. Chou, J.M. Maciejowski: *"System Identification Using Balanced Parametrizations"*; IEEE Trans. Aut. Control, vol. 42, no. 7, July 1997, pp. 956-974.

8. Known properties/peculiarities:

9. Some MATLAB-code to retrieve the data

```
!gunzip dryer.dat.Z
load dryer.dat
U=dryer(:,2:4);
Y=dryer(:,5:7);
```

D008: Liquid-saturated steam heat exchanger (4000 samples, 1 input 1 output)

1. Contributed by:

Sergio Bittanti
Politecnico di Milano
Dipartimento di Elettronica e Informazione,
Piazza Leonardo da Vinci 32, 20133 MILANO (Italy)
bittanti@elet.polimi.it

2. Process/Description:

The process is a liquid-satured steam heat exchanger, where water is heated by pressurized saturated steam through a copper tube. The output variable is the outlet liquid temperature. The input variables are the liquid flow rate, the steam temperature, and the inlet liquid temperature. In this experiment the steam temperature and the inlet liquid temperature are kept constant to their nominal values.

3. Sampling time: 1 s

4. Number of samples: 4000

5. Inputs:

q: liquid flow rate

6. Outputs:

th: outlet liquid temperature

7. References:

S. Bittanti and L. Piroddi: *"Nonlinear identification and control of a heat exchanger: a neural network approach"*; Journal of the Franklin Institute, 1996.
L. Piroddi: *"Neural Networks for Nonlinear Predictive Control"*; Ph.D. Thesis, Politecnico di Milano (in Italian), 1995.

8. Known properties/peculiarities:

The heat exchanger process is a significant benchmark for nonlinear control design purposes, since it is characterized by a non minimum phase behaviour. In the references cited above the control problem of regulating the output temperature of the liquid-satured steam heat exchanger by acting on the liquid flow rate is addressed, and both direct and inverse identifications of the data are performed.

column 1: time-steps
column 2: input q
column 3: output th

D009: Test setup of an industrial winding process (2500 samples; 5 inputs. 2 outputs)

1. Contributed by:

Wouter Favoreel
KULeuven
Departement Electrotechniek ESAT/SISTA
Kardinaal Mercierlaan 94, B-3001 Leuven, Belgium

2. Process/description:

The process is a test setup of an industrial winding process. The main part of the plant is composed of a plastic web that is unwinded from first reel (unwinding reel), goes over the traction reel and is finally rewinded on the the rewinding reel. Reel 1 and 3 are coupled with a DC-motor that is controlled with input setpoint currents I1* and I3*. The angular speed of each reel (S1, S2 and S3) and the tensions in the web between reel 1 and 2 (T1) and between reel 2 and 3 (T3) are measured by dynamo tachometers and tension meters.

We thank Th. Bastogne from the University of Nancy for providing us with these data. We are grateful to Thierry Bastogne of the Universite Henri Point Care, who provided us with these data.

3. Sampling time: 0.1 Sec

4. Number of samples: 2500

5. Inputs:

u1: angular speed of reel 1 (S1)
u2: angular speed of reel 2 (S2)
u3: angular speed of reel 3 (S3)
u4: setpoint current at motor 1 (I1*)
u5: setpoint current at motor 2 (I3*)

6. Outputs:

y1: tension in the web between reel 1 and 2 (T1)
y2: tension in the web between reel 2 and 3 (T3)

7. References:

T. Bastogne: *"Identification des systemes multivariables par les methodes des sous-espaces. Application a un systeme d'entrainement de bande"*; Ph.D. thesis. These de doctorat de l'Universite Henri Poincare, Nancy 1.

T. Bastogne, H. Noura, A. Richard, J.M. Hittinger: *"Application of subspace methods to the identification of a winding process"*; Proc. of the 4th European Control Conference, Vol. 5, Brussels.

8. Known properties:

column 1: input u1
column 2: input u2
column 3: input u3
column 4: input u4
column 5: input u5
column 6: output y1
column 7: output y2

D010: Continuous stirred tank reactor (7500 samples; 1 input, 2 outputs)

1. Contributed by:

Jairo ESPINOSA
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2. Description:

The Process is a model of a Continuous Stirring Tank Reactor, where the reaction is exothermic and the concentration is controlled by regulating the coolant flow.

3. Sampling: 0.1 min

4. Number of samples: 7500

5. Inputs:

q: coolant Flow l/min

6. Outputs:

Ca: concentration mol/l
T: temperature Kelvin degrees

7. References:

J.D. Morningred, B.E.Paden, D.E. Seborg, D.A. Mellichamp: *"An adaptive nonlinear predictive controller"*; Proc. of the A.C.C. vol.2 1990, pp. 1614-1619

G.Lightbody, G.W.Irwin: *"Nonlinear Control Structures Based on Embedded Neural System Models"*; IEEE Trans. on Neural Networks, vol.8, no.3, pp. 553-567

J.Espinosa, J. Vandewalle: *"Predictive Control Using Fuzzy Models"*; 3rd. On-Line World Conf. on Soft Computing in Engineering Design and Manufacturing.

8. Known properties:

column 1: time-steps
column 2: input q
column 3: output Ca
column 4: output T

D011: Model of a steam generator (9600 samples; 4 inputs, 4 outputs)

1. Contributed by:

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jairo.espinosa@esat.kuleuven.ac.be

2. Description:

The data comes from a model of a Steam Generator at Abbott Power Plant in Champaign IL.
The model is described in the paper of Pellegrineti [1].

3. Samplingtime: 3 sec

4. Number of samples: 9600

5. Inputs:

u1: fuel, scaled 0-1
u2: air, scaled 0-1
u3: reference level, inches
u4: disturbance defined by the load level

6. Outputs:

y1: drum pressure, PSI
y2: excess oxygen in exhaust gases, %
y3: level of water in the drum
y4: steam flow, Kg./s

7. References:

G. Pellegrinetti, J. Benstman: *"Nonlinear Control Oriented Boiler Modeling -A Benchmark Problem for Controller Design"*; IEEE Trans. Control Systems Tech., vol.4, no.1, Jan.1996
J. Espinosa, J. Vandewalle: *"Predictive Control Using Fuzzy Models Applied to a Steam Generating Unit"*; FLINS 98 3rd. International Workshop on Fuzzy Logic Systems and Intelligent Technologies for Nuclear Science and Industry

8. Known properties:

To make possible the open loop identification the water level was stabilized by appliying to the water flow input a feedforward action proportional to the steam flow with value 0.0403 and a PI action with values Kp=0.258 Ti=1.1026e-4 the reference of this controller is the input u3.
column 1: time-steps
column 2: input fuel
column 3: input air
column 4: input level ref.
column 5: input disturbance
column 6: output drum pressure
column 7: output excess oxygen
column 8: output water level
column 9: output steam flow

D101: Ball-and-beam setup at SISTA (1000 samples; 1 input, 1 output)

1. Contributed by:

Peter Van Overschee
K.U.Leuven - ESAT - SISTA
K. Mercierlaan 94, 3001 Heverlee, Belgium
Peter.Vanoverschee@esat.kuleuven.ac.be

2. Process/Description:

Data of a the ball and beam practicum at ESAT-SISTA.

3. Sampling time: 0.1 sec.

4. Number of samples: 1000

5. Inputs:

a. angle of the beam

6. Outputs:

a. position of the ball

7. References:

P. Van Overschee: *"Subspace identification: Theory, Implementation, Application"*; Ph. D. Thesis, K.U.Leuven, February 1995, pp. 200-206

8. Known properties/peculiarities

9. Some MATLAB-code to retrieve the data

```
!gunzip ballbeam.dat.Z
load ballbeam.dat
U=ballbeam(:,1);
Y=ballbeam(:,2);
```

D102: Laboratory setup acting like a hair dryer (1000 samples; 1 input, 1 output)

1. Contributed by:

Wouter Favoreel
KULeuven
Departement Electrotechniek ESAT/SISTA
Kardinaal Mercierlaan 94, B-3001 Leuven, Belgium

2. Description:

Laboratory setup acting like a hair dryer. Air is fanned through a tube and heated at the inlet. The air temperature is measured by a thermocouple at the output. The input is the voltage over the heating device (a mesh of resistor wires).

3. Sampling time:

4. Number of samples: 1000

5. Inputs:

u: voltage of the heating device

6.Outputs:

y: output air temperature

7. References:

L. Ljung: *"System identification - Theory for the User"*; Prentice Hall, Englewood Cliffs, NJ, 1987.
L. Ljung: *"System Identification Toolbox. For Use with Matlab"*; The Mathworks Inc., Mass., USA., 1991.

8. Known properties:

column 1: input u
column 2: output y

D103: CD-player arm (2048 samples; 1 input, 1 output)

1. Contributed by:

Wouter Favoreel
KULeuven
Departement Electrotechniek ESAT/SISTA
Kardinaal Mercierlaan 94, B-3001 Leuven, Belgium

2. Description:

Data from the mechanical construction of a CD player arm. The inputs are the forces of the mechanical actuators while the outputs are related to the tracking accuracy of the arm. The data was measured in closed loop, and then through a two-step procedure converted to open loop equivalent data

The inputs are highly colored.

We are grateful to R. de Callafon of the Mechanical Engineering Systems and Control group of Delft, who provided us with these data.

3. Sampling time:

4. Number of samples: 2048

5. Inputs:

u: forces of the mechanical actuators

6. Outputs:

y: tracking accuracy of the arm

7. References:

P. Van Den Hof, R.J.P. Schrama: *"An Indirect Method for Transfer Function Estimation From Closed Loop Data"*; Automatica, vol. 29, no. 6, pp. 1523-1527, 1993.

8. Known properties:

column 1: input u1
column 2: input u2
column 1: output y1
column 2: output y2

D104: Wing flutter data (1024 samples; 1 input, 1 output)

1. Contributed by:

Wouter Favoreel
KULeuven
Departement Electrotechniek ESAT/SISTA
Kardinaal Mercierlaan 94, B-3001 Leuven, Belgium

2. Description:

Wing flutter data. Due to industrial secrecy agreements we are not allowed to reveal more details. Important to know is that the input is highly colored.

3. Sampling time:

4. Number of samples: 1024

5. Inputs:

u:

6. Outputs:

y:

7. References:

E. Feron, M. Brenner, J. Paduano, A. Turevskiy: *"Time-frequency analysis for transfer function estimation and application to flutter clearance"*; AIAA J. on Guidance, Control & Dynamics, vol. 21, no. 3, pp. 375-382, May-June, 1998.

8. Known properties:

column 1: input u
column 2: output y

D105: Flexible robot arm (1024 samples; 1 input, 1 output)

1. Contributed by:

Wouter Favoreel
KULeuven
Departement Electrotechniek ESAT/SISTA
Kardinaal Mercierlaan 94, B-3001 Leuven, Belgium

2. Description:

Data from a flexible robot arm. The arm is installed on an electrical motor. We have modeled the transfer function from the measured reaction torque of the structure on the ground to the acceleration of the flexible arm. The applied input is a periodic sine sweep.

We are grateful to Hendrik Van Brussel and Jan Swevers of the laboratory of Production Manufacturing and Automation of the Katholieke Universiteit Leuven, who provided us with these data, which were obtained in the framework of the Belgian Programme on Interuniversity Attraction Poles (IUAP-nr.50) initiated by the Belgian State - Prime Minister's Office - Science Policy Programming.

3. Sampling time:

4. Number of samples: 1024

5. Inputs:

u: reaction torque of the structure

6. Outputs:

y: accelaration of the flexible arm

7. References:

8. Known Properties:

column 1: input u
column 2: output y

D106: Experiment on a Steel Subframe Flexible structure (8523 samples; 2 inputs, 28 outputs)

1. Contributed by:

Maher ABDELGHANI
IRISA-INRIA
Campus de Beaulieu
35042 Rennes cedex, FRANCE
Maher.Abdelghani@irisa.fr

2. Description:

Experiment on a Steel Subframe Flexible structure performed at LMS-International, Leuven-Belgium.
- Structure suspended with flexible rubber bands.
- 2 shakers at 2 locations were used for force input signals.
- 28 accelerometers around the structure were used for measurements.
- The 30 channels were simultaneously measured using the LMS-CadaX Data Acquisition Module.

3. Sampling time: 1/1024 s

4. Number of samples: 8523 samples/channel

5. Inputs:

u1= white noise force
u2= white noise force.

6. Outputs:

28 outputs: accelerations

7. References:

M.Abdelghani, M.Basseville, A.Benveniste: *"In-Operation Damage Monitoring and Diagnosis of Vibrating Structures, with Application to Offshore Structures and Rotating Machinery"*; IMAC-XV Feb.3-6, 1997, Fl. USA.

M.Abdelghani, C.T.Chou, M. Verhaegen: *"Using Subspace Methods for the Identification and Modal Analysis of Structures"*; IMAC-XV, Feb.3-6, 1997, Fl. USA.

8 Known properties:

frequency range: 10-512 Hz.
column1= input1 (u1)
column2=input2 (u2)
columns3--30: outputs 1-28

D201: Cutaneous potential recordings of a pregnant woman (2500 samples; 8 outputs)

1. Contributed by:

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Departement Electrotechniek ESAT/SISTA
Kardinaal Mercierlaan 94, B-3001 Leuven, Belgium
lieven.delathauwer@esat.kuleuven.ac.be

2. Description:

cutaneous potential recordings of a pregnant woman (8 channels)

3. Sampling time: 5 sec

4. Number of samples: 2500 x 8

5. Inputs:

6. Outputs:

1-5: abdominal
6,7,8: thoracic

7. References:

Dirk Callaerts: *"Signal Separation Methods based on Singular Value Decomposition and their Application to the Real-Time Extraction of the Fetal Electrocardiogram from Cutaneous Recordings"*; Ph.D. Thesis, K.U.Leuven - E.E. Dept., Dec. 1989.

L. De Lathauwer, B. De Moor, J. Vandewalle: *"Fetal Electrocardiogram Extraction by Source Subspace Separation"*; Proc. IEEE SP / ATHOS Workshop on HOS, June 12-14, 1995, Girona, Spain, pp. 134-138.

Jean-Francois Cardoso: *"Multidimensional independent component analysis"*; Proc. ICASSP '98. Seattle, 1998. Available on the net: ftp://sig.enst.fr/pub/jfc/Papers/icassp98.ps More details: http://sig.enst.fr/~cardoso/RRicassp98.html Homepage author: http://sig.enst.fr/~cardoso/stuff.html

8. Known properties:

column 1: time-steps
column 2-9: observations

D202: Tongue displacement shapes occuring in the pronunciation of english vowels

1. Contributed by:

Lieven De Lathauwer
K.U.Leuven, E.E. Dept.- ESAT
K. Mercierlaan 94, B-3001 Leuven (Heverlee), Belgium
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2. Description:

The dataset is a real-valued (5x10x13)-array; basically, it was obtained as follows. High-quality audio recordings and cine-fluorograms were made of five English-speaking test persons while saying sentences of the form ``Sayh({\em vowel})d again" (substitution: ``heed, hid, hayed, head, had, hod, hawed, hoed, hood, who'd"). For each of these 10 vowels an acoustic reference moment was defined and the corresponding 5 (corresponding to the different speakers) frames in the film located. Next, speaker-dependent reference grids, taking into account the anatomy of each test person, were defined and superimposed on the remaining x-ray images. The grids consisted of 13 equidistant lines, in the region from epiglottis to tongue tip, more or less perpendicular to the midline of the vocal tract. The array entries now consist of the distance along the grid lines between the surface of the tongue and the harder upper surface of the vocal tract. The values are given in centimeters and have been measured to the nearest 0.5 mm. For a more extensive description of the experiment, we refer to [1].

3. Sampling time:

4. Number of samples:

5. Inputs:

6. Outputs:

x: speakers
y: vowels
z: positions

7. References:

R. Harshman, P. Ladefoged, L. Goldstein: *"Factor Analysis of Tongue Shapes"*; J. Acoust. Soc. Am., Vol. 62, No. 3, Sept. 1977, pp. 693-707.
L. De Lathauwer: *"Signal Processing based on Multilinear Algebra"*; Ph.D. Thesis, K.U.Leuven, E.E. Dept., Sept. 1997.

8. Properties:

column 1: (speaker number - 1) x 10 + vowel number
columns 2-14: displacement values

D301: Simulation of the western basin of Lake Erie (57 samples; 5 inputs. 2 outputs)

1. Contributed by:

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2. Process/Description:

Data of a simulation (not real !) related to the related to the identification of the western basin of Lake Erie.
The series consists of 4 series:

U_erie, Y_erie: without noise (original series)
U_erie_n10, Y_erie_n10: 10 percent additive white noise
U_erie_n20, Y_erie_n20: 20 percent additive white noise
U_erie_n30, Y_erie_n30: 30 percent additive white noise

3. Sampling time: 1 month

4. Number of samples: 57 samples

5. Inputs:

a. water temperature
b. water conductivity
c. water alkalinity
d. NO3
e. total hardness

6. Outputs:

a. dissolved oxigen
b. algae

7. References:

R.P. Guidorzi, M.P. Losito, T. Muratori: *"On the last eigenvalue test in the structural identification of linear multivariable systems"*; Proc. Vth European Meeting on Cybernetics and Systems Research, Vienna, April 1980.

8. Known properties/peculiarities

The considered period runs from march 1968 till november 1972.

9. Some MATLAB-code to retrieve the data

```
!guzip erie.dat.Z
load erie.dat
U=erie(:,1:20);
Y=erie(:,21:28);
U_erie=U(:,1:5);
U_erie_n10=U(:,6:10);
U_erie_n20=U(:,11:15);
U_erie_n30=U(:,16:20);
Y_erie=Y(:,1:2);
Y_erie_n10=Y(:,3:4);
Y_erie_n20=Y(:,5:6);
Y_erie_n30=Y(:,7:8);
```

D401: Heat flow density through a two layer wall (1680 samples; 2 inputs, 1 output)

1. Contributed by:

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2. Description:

Heat flow density through a two layer wall (brick and insulation layer). The inputs are the internal and external temperature of the wall. The output is the heat flow density through the wall.

3. Sampling time:

4. Number of samples: 1680

5. Inputs:

u1: internal wall temperature
u2: external wall temperature

6. Outputs:

y: heat flow density through the wall

7. References:

System Identification Competition, Benchmark tests for estimation methods of thermal characteristics of buildings and building components. Organization: J. Bloem, Joint Research Centre, Ispra, Italy, 1994.

8. Properties:

column 1: input u1
column 2: input u2
column 3: output y

D402: Heating system (801 samples; 1 input, 1 output)

1. Contributed by:

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2. Process/Description:

The experiment is a simple SISO heating system. The input drives a 300 Watt Halogen lamp, suspended several inches above a thin steel plate. The output is a thermocouple measurement taken from the back of the plate.

3. Sampling interval: 2.0 seconds

4. Number of samples: 801

5. Inputs:

u: input drive voltage

6. Outputs:

y: temperature (deg. C)

7. References:

Geir Dullerud & Roy Smith: *"Sampled Data Model Validation: an Algorithm and Experimental Application"*; Intern. Journal of Robust and Nonlinear Control, vol. 6, no. 9-10, pp. 1065-1078, 1996.

8. Known properties/peculiarities

The data (and nominal model) is the above paper have the output expressed in 10's deg. C. This has been rescaled to the original units of deg. C. in the DaISy data set. There is also a -1 volt offset in u in the data shown plotted in the original paper. This has been removed in the DaISy dataset. The data shows evidence of discrepancies. One of the issues studied in the above paper is the size of these discrepancies - measured in this case in terms of the norm of the smallest perturbation required to account for the difference between the nominal model and the data. The steady state input (prior to the start of the experiment) is u = 6.0 Volts.

D501: Simulator of in-vivo MRS signals

1. Contributed by:

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2. Process/Description:

This simulation signal is derived from a typical in-vivo 31P spectrum measured in the human brain and consists of 11 exponentials. The 31P peaks from brain tissue, phosphomonoesters, inorganic phosphate, phosphodiesters, phosphocreatine, Gamma-ATP, Alpha-ATP and Beta-ATP are present in this simulation signal.

3. Sampling time: 0.333 msec.

4. Number of samples; the user can choose. Typical values however range from 256 to 1024.

5. Inputs:

6. Outputs:

7. References:

L. Vanhamme, A. van den Boogaart, S. Van Huffel: *"Fast and accurate parameter estimation of noisy complex exponentials with use of prior knowledge"*; Proc. EUSIPCO-96, Sept. 10-13, 1996, Trieste, Italy.
L. Vanhamme, A. van den Boogaart, S. Van Huffel: *"Improved Method for Accurate and Efficient Quantification of MRS Data with Use of Prior Knowledge"*; January 1997, Journal of Magnetic Resonance; also ESAT/SISTA report 97-02.

8. Known properties

9. Some MATLAB-code to retrieve the data

The user can of course change the number of data point used to construct the data. He can als add noise with any desired standard deviation as described in the .m file.

D601: One hour of internet traffic between Lawrence Berkeley Laboratory and the rest of the world (99999 samples; 1 output)

1. Contributed by:

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2. Description:

one hour of internet traffic between the Lawrence Berkeley Laboratory and the rest of the world

3. Sampling time:

4. Number of samples: 99999

5. Inputs:

6. Output: number of packets per time unit

7. References:

Katrien De Cock, Bart De Moor: *"Identification of the first order parameters of a circulant modulated Poisson process"*; Proc. of the Intern. Conf. on Telecommunication (ICT '98)

V. Paxson, S. Floyd: *"Wide-area traffic: The failure of Poisson modeling"*; IEEE/ACM Trans. on Networking, 1995

8. Known properties:

column 1: time-steps
column 2: output y