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1. Introduction to the department

ELEC

1.1 INTRODUCTION TO THE LONG TERM STRATEGY OF THE DEPARTMENT ELEC

‘ELEC’ stands for “Fundamental Electricity and Instrumentation” (in Dutch: “Algemene Elektriciteit en Instrumentatie”) and the name corresponds to the educational and research tasks and objectives of the department. The main research activity of the department is the development of new measurement techniques using advanced signal processing methods, embedded in an identification framework. When we make a measurement, we have to make a number of decisions: firstly a model for the considered part of reality is proposed (e.g. for a resistance measurement Ohm’s law can be selected, describing the relation between the voltage across the resistor and the current through it); next a number of measurements is made (e.g. a number of current and voltage measurements); finally the quantities of interest are extracted from these measurements by matching the model to the data. Often an intuitive approach is used. However, in the presence of measurement errors this can lead to a very poor and even dangerous behaviour: the user wouldn’t remark that something is going seriously wrong. This is the major motivation for the development of the identification theory. It offers a systematic approach to ‘optimally’ fit mathematical models to experimental data, eliminating stochastic distortions as much as possible. As such it can be considered as the modern formulation of the measurement problem, and for that reason the identification approach is the “fil rouge” in most of the activities of the department.

Each measurement (or identification session) consists of a series of basic steps:

- Collect information about the system;
- Select a (non) parametric model structure to represent the system;
- Select the model parameters to fit the model as well as possible to the measurements (this requires a “goodness of fit” criterion);
- Validate the selected model.

Most of the research activities of the department are related to one of these problems, but this does not narrow our focus. At this moment we deal with a very wide scope of application fields:

- Systems covering the frequency range from a few mHz up to 50 GHz,
- Linear systems and non-linear systems,
- Lumped systems and distributed systems.
We applied the measurement and modelling techniques to the identification of electrical machines (frequency range 0.01 Hz till 1 kHz, linear models, 2 inputs and 2 outputs), mechanical vibrating systems (frequency range below 5 kHz, linear or non-linear, up to 2 inputs/2 outputs), electronic circuits and filters (frequency range up to 5 MHz, linear and non-linear models, single input/single output or multiple input/multiple output), underwater acoustics (frequency range up to a few MHz, 1 input and 2 outputs), distributed systems (telecommunication lines, up to a few hundreds MHz), microwave applications (frequency range up to 50 GHz, non-linear, 6-port measurements). Since a few years we apply those methods also to the analysis of biological samples used as records of global climate change. For some of these applications the efforts are focused on the development of new measurement instruments (measurement of telecommunication lines, non-linear microwave analyser), for others we focused completely on the development of new data processing and modelling techniques, or even worked on the underlying fundamental theoretical aspects.

To cover this wide application range, we make use of an extensive measurement park. Most of it nowadays consists of VXI-based data-acquisition systems, although we have also some classical instruments like network and spectrum analysers. All these instruments are computer controlled in a Matlab™ environment.

1.2 RESEARCH TEAMS OF THE DEPARTMENT ELEC: OVERVIEW OF THE 5 TEAMS

1.2.1 Team A: Automatic Measurement Systems, Telecommunications and Laboratory of Underwater Acoustics.

- Identification of distributed systems
- Incorporation of knowledge engineering in complex measurement problems
- Application of information theory in data telecommunication by wire problems (xDSL)
- Modelling and Identification of transmission lines and wireless channels (LOS and NLOS)
- Wireless local loop
- Signal processing techniques related to measurement in Earth Science problems
- Development of PC and PXI based instrumentation
- Underwater acoustic studies
- Environmental G.I.S. development
- 4G communication
- Navigation techniques, including but not limited by, applications for Location Based Services
- Positioning Techniques using the cellular network (focus on GSM)
- Proactive Location-based Services (LBS) using multiple positioning technologies.
1.2.2  **Team B: System Identification and Parameter Estimation of Linear and Non-Linear Systems**

- Study and development of basic concepts on identification theory
- Identification of linear and nonlinear concentrated and distributed systems
- Experiment design
- Time and frequency domain system identification
- Development and distribution of a system identification toolbox

1.2.3  **Team C: Applied Signal Processing for Engineering (ASPE)**

- Instrumentation setup contributions.
- Instrumentation calibration contributions.
- Modelling high frequency nonlinear systems

1.2.4  **Team D: Medical Measurements and Signal Analysis (M2ESA)**

- Development of customized measurement setups
- Pre/post - processing of medical measurement data
- User-friendly guidelines to accurate and practical signal analysis
- Customized linear and nonlinear modeling techniques for medical and high-frequency applications

1.2.5  **Team E: Identification of Biogeochemical Signals & Systems (IBiSS)**

- Pre- and post-signal processing of solid substrate measurements
- Parameter estimation and constrained optimization of climatological and ecological models
- Validation of environmental models

The department ELEC is attached to the Faculty of Engineering of the "Vrije Universiteit Brussel" (Brussels Free University).

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1.3 THE ELEC FUTSAL TEAM

The mixed girls/boys ELEC futsal team was founded in September 2010, and sponsored by the ELEC department. Some intensive recruiting and scouting work was necessary to get a very motivated team together. The goal of the first season was to establish a good team spirit with the support of our international supporter clan.

The lack of talent is abundantly compensated by the tremendous enthusiasm of the team. We organized some training sessions in order to clarify the rules and possible tactics of the game. Only one mistake later everyone knew which way the ball had to go. This resulted in some nice goals, but sadly enough only one win up to now – a forfeit of the opponent. We expect that in the near future more wins will follow now we established some team tactics, and our talent starts to develop.
1.4 STAFF OF ELEC (STATUS 01/02/2011)

1.4.1 General director

Johan Schoukens (head of the department) received the degree of Electrical Engineer, and the degree of doctor in applied sciences, from the Vrije Universiteit Brussel (VUB), Brussels, Belgium in 1980 and 1985, respectively. Until September 2000 he was a Research Director of the Fund for Scientific Research - Flanders (FWO) and part time lecturer at the VUB in the Electrical Measurement Department (ELEC). Presently he is a full time professor at the same department (ELEC). His research interests are in the field of identification of linear and nonlinear systems.

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1.4.2 Team A: Automatic Measurement systems, Telecommunications and Laboratory of Underwater Acoustics

Leo Van Biesen (coordinator of team A) was born in Elsene, Belgium, on August 31, 1955. He received the degree of Electro-Mechanical Engineer from the Vrije Universiteit Brussel (VUB), Brussels in 1978, and the Doctoral degree (PhD) from the same university in 1983. Currently he is a full senior professor. He teaches courses on fundamental electricity, electrical measurement techniques, signal theory, computer-controlled measurement systems, telecommunication, underwater acoustics and Geographical Information Systems for sustainable development of environments. His current interests are signal theory, modern spectral estimators, time domain reflectometry, wireless local loops, xDSL technologies, underwater acoustics, and expert systems for intelligent instrumentation. He has been chairman of IMEKO TC-7 from 1994-2000 and President Elect of IMEKO for the period 2000-2003 and the liaison Officer between the IEEE and IMEKO. Prof. Dr. Ir. Leo Van Biesen has been president of IMEKO until September 2006. He is also member of the board of FITCE Belgium and of USRSI Belgium.

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Hernan Cordova was born in Guayaquil, December 19, 1977. In October 1999 he obtained graduated as a Bachelor of Science in Electrical Engineering at the Escuela Superior Politecnica del Litoral (ESPOL), Guayaquil. In august 2004, he finished at the same university a master degree program in Tele-communications Management. Since september 2004, he is going towards the PhD at the ELEC department being supervised by Prof. Van Biesen. His main interests are: Digital Signal processing and Fixed and Mobile Wireless Communications.

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Wim Foubert was born in Geraardsbergen, on February 14, 1983. In July 2006, he received the degree of Electrical Engineering (option Electronics and Information Processing) from the Vrije Universiteit Brussel (VUB). He joined the department ELEC in December 2006, as a PhD student. His main research interests are on the design of new transmission channel models for xDSL systems.

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Carine Neus was born in Anderlecht, Belgium, on March 16, 1983. She graduated as an Electrical Engineer (Burgerlijk Elektrotechnisch Ingenieur), option Telecommunication in July 2004 at the Vrije Universiteit Brussel. Carine joined the department ELEC as a research assistant on October 1st, 2004. Her main research is on the estimation of the line capacity with Single Ended Line Testing (applied to xDSL technologies).

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1.4.3 Team B: System Identification and Parameter Estimation of Linear and Nonlinear Systems

Johan Schoukens (Coordinator Team B) received the degree of Electrical Engineer, and the degree of doctor in applied sciences, from the Vrije Universiteit Brussel (VUB), Brussels, Belgium in 1980 and 1985, respectively. Until September 2000 he was a Research Director of the Fund for Scientific Research - Flanders (FWO) and part time lecturer at the VUB in the Electrical Measurement Department (ELEC). Presently he is a full time professor at the same department (ELEC). His research interests are in the field of identification of linear and nonlinear systems.

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Michel Gevers was born in Antwerp, Belgium, in 1945. He obtained an Electrical Engineering degree from the Université Catholique de Louvain, Belgium, in 1968, and a Ph.D. degree from Stanford University, California, in 1972. He holds a Honorary Degree from the Vrije Universiteit Brussel and the University of Linköping, Sweden, and a few other titles. He has been President of the European Union Control Association (EUCA) from 1997 to 1999, and Vice President of the IEEE Control Systems Society in 2000 and 2001. Between 1990 and 2010 he has been the coordinator of the Belgian Interuniversity Network DYS CO (Dynamical Systems, Control, and Optimization) funded by the Federal Ministry of Science. His research interests are in system identification and its interconnection with robust control design, optimal experiment design, data-based control design, optimal control and filtering, and realization theory. He has published about 250 papers and conference papers, and two books: "Adaptive Optimal Control - The Thinking Man's GPC", by R.R. Bitmead, M. Gevers and V. Wertz (Prentice Hall, 1990), and "Parametrizations in Control, Estimation and Filtering Problems: Accuracy Aspects", by M. Gevers and G. Li (Springer-Verlag, 1993). Currently he is 20% active at the department ELEC as Professor emeritus.

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John Lataire was born in Etterbeek (Belgium) in 1983. He graduated as an Electrical Engineer in Electronics and Information Processing (profile Measurement and Modelling of Dynamic Systems) in July 2006 at the Vrije Universiteit Brussel. In August 2006 he joined the department ELEC as a PhD student. His main interests are the measurement and identification of slowly time varying, weakly nonlinear dynamic systems.

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Ebrahim Louarroudi was born in Antwerp (Mortsel), Belgium, on May 29, 1985. He received the degree of Electromechanical Engineering in July 2009 from the Vrije Universiteit Brussel, Brussels, Belgium. He joined the department ELEC as a PhD Student in October 2009. His main interests are the measurement and frequency domain identification of linear periodically time-Varying systems.

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Anna Marconato was born in Trento, Italy, on April 8th, 1980. She received the B.Sc. in Mathematics and the M.Sc. in Telecommunication Engineering from the University of Trento, Italy, in 2002 and 2005, respectively. In 2009 she was awarded a joint PhD degree from the University of Trento, Italy, and the Vrije Universiteit Brussel, Belgium. From September 2009 she has been a post-doctoral researcher at Department ELEC, Vrije Universiteit Brussel, Belgium. Her main research interests are in the fields of nonlinear system identification and machine learning.

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David Oliva Uribe was born on May 24th 1975, Mexico City, Mexico. His research interests are in the field of system identification techniques for piezoelectric transducers, in particular the characterization of biological tissues using tactile sensors in medical applications. He graduated with Honours in Electronic and Communication Engineering in 1997 and obtained a Master in Sciences with Specialization in Manufacturing Systems in 2000, both from Tecnológico de Monterrey in Mexico City. From April 2007 to December 2010 he worked as Team Leader of the Research Group of Medical Engineering and Mechatronic Systems at the Institute of Dynamics and Vibrations Research from the Leibniz University of Hannover. Since January 2011, he joined the Department ELEC, Vrije Universiteit Brussel, where he is working toward a joint PhD degree.

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Rik Pintelon was born in Gent, Belgium, on December 4, 1959. He received the degree of Electrotechnical-Mechanical Engineer (burgerlijk ingenieur) in July 1982, the degree of doctor in applied science in January 1988, and the qualification to teach at university level (geaggregeerde voor het hoger onderwijs) in April 1994, all from the Vrije Universiteit Brussel (VUB), Brussels, Belgium. Until September 2000 he was a Research Director of the Fund for Scientific Research - Flanders (FWO) and part time lecturer at the VUB in the Electrical Measurement Department (ELEC). Presently he is a full time professor at the same department (ELEC). His main research interests are in the field of parameter estimation / system identification, and signal processing.

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Mattijs Van de Walle was born in Bonheiden on the 25th of October, 1979. He received an engineering degree in electronics from the ‘De Nayer instituut’, Sint Katelijne Waver, Belgium, in 2002. After teaching electronics and telecommunication at the Vrij Technisch Instituut (VTI), leuven, for two years, he took up studying again to receive the degree of electrical engineer from the Vrije Universiteit Brussel (VUB), Brussels, Belgium, in 2007. Currently, he is working as a PhD research student at the VUB, department ELEC. The aim of his research is the analysis of flutter in a non-linear framework.

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Anne Van Mulders was born in Jette on September 19, 1984. In July 2007, she received the degree of Mechanical Engineering from the Vrije Universiteit Brussel. She joined the department of ELEC in September 2007 as a PhD student. Her main research interests are in the field of nonlinear system identification.

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David Westwick received the BASc. in Engineering Physics from The University of British Columbia, the MScE. in Electrical Engineering from The University of New Brunswick, and the PhD. in Electrical Engineering from McGill University. These were followed by Post-Doc appointments at Boston University and TU Delft. He is currently taking a sabbatical leave from the Department of Electrical and Computer Engineering at the University of Calgary, where he is an Associate Professor.

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Dhammika Widanage was born on November 3rd 1983, Kuwait City, Kuwait. His research interests are in the fields of system identification, in particular the effects of nonlinearities on process models, multiple input multiple output systems and of control. He was awarded a Ph.D. in 2008 for research done in the Systems Modelling and Simulation Research Group and graduated with a First-Class Honours in Electronic and Communication Engineering in 2004 (BEng - Bachelor of Engineering) both from the University of Warwick, UK. From June 2008 he has been a Postdoctoral Research Fellow in the System Identification and Parameter Estimation Research Team in the Department of Fundamental Electricity and Instrumentation at the Vrije Universiteit Brussel.

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1.4.4 Team C: Applied Signal Processing for Engineering (ASPE)

Gerd Vandersteen (coordinator of team C) was born in Belgium in 1968 and received the degree in electrical engineering from the Vrije Universiteit Brussel (VUB), Brussels, Belgium, in 1991. In 1997, he received his PhD in electrical engineering, entitled “Identification of Linear and Nonlinear Systems in an Errors-in-Variables Least Squares and Total Least Squares Framework”, from the Vrije Universiteit Brussel/ ELEC. During his postdoc, he worked at the micro-electronics research centre IMEC as Principal Scientist in the Wireless Group with the focus on modeling, measurement and simulation of electronic circuits in state-of-the-art silicon technologies. This research was in the context of a collaboration with the Vrije Universiteit Brussels. From 2008 on, he is working as Prof. at the Vrije Universiteit Brussels/ELEC within the context of measuring, modeling and analysis of complex linear and nonlinear systems. Within this context, the set of systems under consideration is extended from micro-electronic circuits towards to all kinds of electro-mechanical systems.

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Alain Barel was born in Roeselare, Belgium, on July 27, 1946. He received the degree in Electrical Engineering from the Université Libre de Bruxelles, Belgium, in 1969, the Postgraduate degree in telecommunications from Rijks Universiteit Gent (State University of Gent), Belgium, in 1974, and the doctor of applied science from the Vrije Universiteit Brussel in 1976. He worked as assistant and Lecturer at the Vrije Universiteit Brussel (VUB). Currently he is 10% active at the department as Professor emeritus and teaches microwaves.

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Diane De Coster was born in Etterbeek (Belgium) in 1987. She graduated as an Electrical Engineer in Electronics and IT-Engineering (profile Photonics) in July 2010 at the Vrije Universiteit Brussel. In October 2010 she joined the department ELEC as a PhD student. Her main interests are the application of advanced signal processing and measurement techniques to measure the biological composition of fresh water lakes.

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Maulik Jain was born in India on February 4, 1987. He received the Integrated Dual Degree (Bachelor of Technology and Master of Technology) in Electronics and Communication Engineering from Indian Institute of Technology, Roorkee, India in June 2010. He joined the department ELEC of VUB in September 2010 as a PhD researcher. His topic of research is "Linear and Non Linear Modeling for Analog IC design".

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Yves Rolain (1961, Belgium) received the Electrical Engineering (Burgerlijk Ingenieur) degree in July 1984, the degree of computer sciences in 1986, and the PhD degree in applied sciences in 1993, all from the Vrije Universiteit Brussel (VUB), Brussels, Belgium. He is currently a research professor at the VUB in the department ELEC. His main interests are microwave measurements and modelling, applied digital signal processing and parameter estimation / system identification.

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Maarten Schoukens was born in Jette (Belgium) in 1987. He graduated as an Electrical Engineer in Electronics and Information Processing (profile Measurement and Modelling of Dynamic Systems) in July 2010 at the Vrije Universiteit Brussel. In September 2010 he joined the department ELEC as a PhD student. His main interests are in the field of nonlinear block oriented system identification of multiport microwave systems.

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Diana Ugryumova was born in Kiev, Ukraine, on October 26th, 1984. She received the degree in Applied Mathematics (chair of Mathematical Theory of Systems and Control) at the University of Twente in the Netherlands in March 2010. Diana joined the department of ELEC in May 2010 as a PhD student. Her current research is about identification of distillation columns. The aim of this research is to enhance the performance of a distillation column through a better modeling and control strategy.

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Team D: Medical Measurements and Signal Analysis (M2ESA)

Wendy Van Moer (coordinator Team D), (12/07/1974), received the Engineer and Ph. D. degrees in Engineering from the Vrije Universiteit Brussel (VUB), Brussels, Belgium, in 1997 and 2001, respectively. She is currently a part time lecturer with the Electrical Measurement Department (ELEC), VUB and a post-doctoral researcher of the Research Foundation-Flanders (FWO). Her main research interests are nonlinear measurement and modeling techniques for medical and high-frequency applications. She was the recipient of the 2006 Outstanding Young Engineer Award from the IEEE Instrumentation and Measurement. Since 2007 she has been an associate editor for the IEEE Transactions on Instrumentation and Measurement and in 2010 she became an associate editor of the IEEE Transactions on Microwave Theory and Techniques.

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Kurt Barbé Kurt Barbé was born in Aalst on April 25, 1983. He received the degree in Mathematics (option Statistics) and the PhD degree in electrical engineering from the Vrije Universiteit Brussel (VUB), Brussels, Belgium, in 2005 and 2009 respectively. Presently, he is working as a post-doctoral researcher at the VUB, department ELEC. His main interests are in the field of System Identification, time series and its finite sample properties.

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Per Landin received the M.Sc. in engineering physics from Uppsala University in 2007 and the lic. tech. (teknologie licentiat) in telecommunications from KTH/Royal Institute of Technology in 2009. He is currently working towards a joint Ph.D. with the VUB, ELEC department, and KTH, signal processing department. His main research interests are in the field of modeling and correction of nonlinear high frequency devices, and high frequency measurement systems.

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Lieve Lauwers was born in Jette, Belgium, on March 15, 1982. She received the degree of Electrical Engineering (option Photonics) in 2005 from the Vrije Universiteit Brussel (VUB), Brussels, Belgium. In August 2005 she joined the department ELEC of the VUB as a PhD student. Her research interests are in the field of nonlinear system identification.

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Charles Nader was born in Lebanon, on July 11, 1982. He received an M.E. in electrical engineering from the Lebanese University ULFG2, Lebanon, in 2005 and an M.Sc in EE/Telecommunication from the University of Gävle, Sweden in 2006. In 2007, he was a consultant for Multilane inc. in Lebanon, working with microwave devices and signal integrity. In 2008, he joined the University of Gävle, center for RF measurement technology, and the Royal Institute of Technology, signal processing lab, Sweden, where he is currently working on his Ph.D. with a research focus on improving radio frequency systems performance by digital signal processing. In 2010, he received the degree of Licentiate of Engineering in Telecommunication/Signal Processing from the Royal Institute of Technology. In 2010, he also joined the Vrije Universiteit Brussel, ELEC Department, Belgium, where he is working toward a double PhD degree.

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Oscar J. Olarte Rodríguez was born in Colombia, March 31, 1980. In June 2004 he received the degree of Electronic Engineer from the Universidad Industrial de Santander (UIS). In September 2007, he obtained in the same University his Master degree in Electronic Engineer. In November he joined department ELEC at the Vrije Universiteit Brussel (VUB) for his PhD. His main research interests are in the field of signal processing and time series.

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Kevin Voet was born in Jette (Belgium) in 1987. He graduated as an Electrical Engineer in Electronics and Information Communication Technology in June 2010 at the Artesis Hogeschool Antwerpen. In August 2010 he joined the department ELEC as a PhD student. His main interests are RF engineering and H.F. Measurements.

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1.4.5 Team E: Identification of Biogeochemical Signals & Systems (IBiSS)

Maité Bauwens was born in Butare (Rwanda), on December 18, 1982. She received the degree in biology, option environmental biology, in July 2005 from the Vrije Universiteit Brussel (VUB), Brussels, Belgium. In November 2005 she joined the department ELEC of the VUB. Presently she is working as a PhD research student under the supervision of Johan Schoukens and Frank Dehairs (Dept. Chemistry/VUB). Her research is in collaboration with the CALMARS project and is focused on applications of system identification techniques in the climate reconstruction.

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Veerle Beelaerts was born in Brugge, Belgium, on February 27, 1981. She graduated as a bio-engineer in Chemistry in 2005 at the Vrije Universiteit Brussel (VUB), Belgium. Presently she is working as a PhD research assistant under the supervision of Johan Schoukens, Frank Dehairs and Rik Pintelon. Her research is in collaboration with the CALMARS project and is focused on identification of biochemical systems and signals.

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1.4.6 Technical and Administrative Staff

Wim Delcourte

Wim Delcourte was born in 1962 (Belgium). He graduated as an Industrial Engineer (Industrieel Ingenieur) in 1987. Since May 1989 he is with the department ELEC of the Vrije Universiteit Brussel (VUB full time tenure). Actually he is responsible for the design of electronic measurement instruments for research and education, for the repair and maintenance of complex measurement instruments and computers (20%). He also takes care of the management of the computerrooms of the faculty (80%).

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Jenny Lievens

Jenny Lievens was born on December 12, 1953 (Brussels, Belgium). She graduated from secretary school in 1971. Since October 1971 she is with the department ELEC (actually part-time). She is mainly responsible for the general secretariat and accounting of the department. Besides, she organises the social activities for the ELEC members.

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Johan Pattyn

Johan Pattyn was born in 1974 (Belgium). After 2 years of engineering studies he joined the navy to become a radar technician. Since december 2009 he is with the department ELEC of the Vrije Universiteit Brussel (full time tenure). He is responsible for Rapid PCB Prototyping and also is involved in the maintenance and repair of the instruments and circuits for the students lab’s.

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Ann Pintelon

Ann Pintelon was born in October 1963 (Belgium). In 1985 she received the Ms degree in Physical Education (VUB). Since 1990 she has been with the department ELEC at the Vrije Universiteit Brussel on a GOA contract (Measurement, Modelling and Identification of Dynamic Systems), and since 2008 she is working on "Methusalem": Centre for Data Based Modelling and Model Quality Assessment (4/5 tenure). She is mainly responsible for the scientific reports of the department ELEC (annual report, web-pages ELEC, ...); the management of the infocentre (library, publication list, ...); the administrative organisation of conferences and workshops; hosting of visiting researchers; and administrative support to the associated editor of Automatica in the dept. ELEC.

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Sven Reyniers

Sven Reyniers was born in 1973 (Belgium). He has several years of ICT - experience in multinationals, including several international missions (France, Germany). Since 2006, he is working at the Vrije Universiteit Brussel (full time tenure) at the department ELEC. As system and network administrator he is responsible for the health and availability of the department servers and network.

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1.4.7 Professors Emeriti

**Alain Barel.** (see 1.4.4)

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**Michel Gevers** (see 1.4.3)

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**Ronny Van Loon.** Born in Antwerp, 1940, he obtained a degree in Physics at the ULB, and a PhD in Science at the VUB. He joined the VUB in 1970 as assistant, then Professor at the Faculty of Applied Science. In parallel with the teaching activities, he had research and logistic activities as a medical physicist at the university hospital AZ-VUB: from 1982 on in the Radiotherapy department focusing on EC granted projects in Hyperthermia, from 1989 on in the Radiology department involved in dosimetry and quality assurance. He directed the subgroup QUARAD (“Quality in Radiology”), a team involved in dosimetry, radiation protection and quality improvement in radiology. This group is acting in Belgium as reference centre for the Quality Assurance of the technical aspects of breast cancer screening. Prof. Van Loon is the Past-President of the Belgian Hospital Physicist Association, and member of the Board of the “Federal Agency of Nuclear Control” and the “Belgian Society of Radioprotection”. He was delegate of the VUB in the VLIR-cooperation and Development Cell, and coordinates a cooperation project in Hanoi (Vietnam) and in VLIR International Training programme on Medical Physics. Until September 2005, he was still 10% active at the department ELEC as professor emeritus. He also contributes to the IAEA’s (International Atomic Energy Agency) teaching programs on radiation protection in medical applications of ionizing radiation. Presently he is scientific advisor at the “Belgian Museum of Radiology”, Brussels, and he is active as a voluntary researcher at the dept. ELEC. In October 2008, he received the title of "Doctor Honoris Causa" from the Hanoi University of Technology.  
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1.4.8 List of phone numbers and e-mail addresses (Status 01/01/2010)

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</tbody>
</table>
1.4.9 PhD-students from other departments, universities, institutions...

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- MSc Indira NOLIVOS, ESPOL, Equador: Promoter: L. Van Biesen
- ir. Mirko SCHOLZ, IMEC-Leuven, promoter: G. Vandersteen and D. Linten (IMEC)

1.4.10 Industrial Partnership

- Dr. ir. Alain GEENS, BeIV
- ir. Frank LOUAGE, MSc Zobeida Cisneros Barros; Address Systems N.V.
- Dr. ir. Luc PEIRLINCKX, Phonetics Topographics, Belgium
- Lic. Marc PERSOONS, Tresco Navigation Systems
- ir. Serge TEMMERMAN, SEBA service nv (measuring instruments for telecom. cables)
- Dr. Frank UYTDENHOUWEN, Banana-Telecom
- Dr. ir. Marc VANDEN BOSSCHE, Dr. ir. Frans Verbeyst; NMDG Engineering bvba

1.4.11 National or international contacts

1.4.11.1 Visiting professors/researchers

- Ramon BRAGOS, Universitat Politechnica de Catalunya (UPC), Barcelona, Spain: 09/05/2010 – 10/05/2010
- Michel GEVERS, Université Catholique de Louvain, CESAME, Louvain-la-Neuve: 24/03/2010 – 25/03/2010. Microsymposium on system identification and 19/05/2010: Presentation: "Optimal experiment design for open and closed loop identification"

• Justin JACKSON, The University of Michigan, Ann Arbor, USA: 04/06/2010 – 03/07/2010. Doctoral school VUB - dept. ELEC: Identification of Nonlinear Dynamic Systems

• Ketan KANOONGO, Indian University of Technology Kharagpur, West Bengal India: 10/05/2010 – 02/07/2010. Doctoral school VUB - dept. ELEC: Identification of Nonlinear Dynamic Systems


• Mikaya LUMORI, University of San Diego, Electrical Engineering, San Diego, CA, USA, 28/5/2010 – 28/8/2010


• Elias PRZEMYSLAW, AGH University of Science and Technology, Krakow, Poland: 10/08/2010 – 29/09/2010, IAESTE The International Association for the Exchange of Students for Technical Experience

• David RIJLAARSDAM, Eindhoven University of Technology, Control and Systems Technology: 01/10/2010 - 31/12/2010: Cotutelle agreement

• Verena RUPP, KIT - Karlsruhe Institute of Technology, Karlsruhe, Germany: 01/09/2010 – 15/01/2011, IAESTE The International Association for the Exchange of Students for Technical Experience


• Piysh SHARMA, Indian University of Technology Kanpur, India: 07/05/2010 – 02/07/2010. Doctoral school VUB - dept. ELEC: Identification of Nonlinear Dynamic Systems

• Chris STEWART, University of San Diego, Electrical Engineering, California, USA: 04/06/2010 – 03/07/2010. Doctoral school VUB - dept. ELEC: Identification of Nonlinear Dynamic Systems


• Paul VAN DEN HOF, Signals, Systems and Control Group, Department of Applied Physics, Delft University of Technology, Delft, The Netherlands: 24/03/2010 – 25/03/2010. Microsymposium on system identification
• **David WESTWICK**, Department of Electrical and Computer Engineering, University of Calgary, Canada: 17/05/2010 – 22/05/2010. Presentation “Nonlinear system identification as a tool for investigating neuromuscular control systems”

• **Hin Kwan WONG**, University of Warwick, School of Engineering, Coventry, United Kingdom: 06/06/2010 – 02/07/2010. Doctoral school VUB - dept. ELEC: Identification of Nonlinear Dynamic Systems


### 1.4.11.2 Scientific missions

- **Kurt BARBÉ**
  30/03/2010 01/04/2010 Participating at the 29th Benelux Meeting on System and Control, Heeze, The Netherlands
  01/05/2010 06/05/2010 I*MTC 2010, International Instrumentation and Measurement Technology Conference, Austin, Texas: Presentation of paper “Robust small sample properties for likelihood based confidence regions”
  31/05/2010 31/05/2010 IUAP/PAI DYSCO Study day, Gent, het Pand,: Presentation of poster “Linearizing oscillometric blood pressure measurements: (non)sense?”
  28/10/2010 29/10/2010 Participating at IUAP/PAI DYSCO workshop, Louvain-la-Neuve, Château-Ferme de Profondval

- **Maite BAUWENS**
  25/07/2010 29/07/2010 2nd Sclerocronology Conference, Mainz, Germany: Presentation of paper "Which proxies should be integrated in a multi-proxy model?"

- **Veerle BEELAERTS**
  04/06/2010 08/06/2010 Nederlands Instituut voor Onderzoek der Zee (NIOZ): Measurement (stable isotopes)
  25/07/2010 29/07/2010 2nd Sclerocronology Conference, Mainz, Germany: Presentation of paper "Periodic time-series modeling with guaranteed positive growth rate estimation for environmental records"

- **Lynn BOS**
  04/01/2010 31/05/2010 Stanford University, Mixed-signal Group, USA: design and layout of a ΔΣ modulator

- **Ludwig DE LOCHT**
  28/10/2010 29/10/2010 Participating at the IUAP/PAI DYSCO workshop, Louvain-la-Neuve, Château-Ferme de Profondval

- **Arnd GEIS**
  23/05/2010 30/05/2010 IEEE MTT-S Symposium, Annaheim, California: Presentation of paper “An 0.045mm2 0.1-6GHz reconfigurable multi-band, multi-gain LNA for SDR”

- **John LATAIRE**
  01/02/2010 04/02/2010 IMAC-XXVIII conference, Jacksonville, Florida USA: Presentation of paper "Frequency Domain Tracking of Time-Varying Modes"
  30/03/2010 01/04/2010 29th Benelux Meeting on System and Control, Heeze, The Netherlands: Presentation of paper: "Frequency Domain Total Least Squares Estimator..."
Annual report ELEC 2010

04/07/2010 10/07/2010 19th International Symposium on Mathematical Theory of Networks and
Systems”

31/05/2010 31/05/2010 Participating at the IUAP/PAI DYSCO Study day, Gent, het Pand

07/09/2010 10/09/2010 Participating at the UKACC International Conference on CONTROL 2010,
Coventry, UK

domain total least squares estimator of linear, time-varying systems”

28/10/2010 29/10/2010 Participating at the IUAP/PAI DYSCO workshop, Louvain-la-Neuve,
Château-Ferme de Profondval

14/12/2010 20/12/2010 49th IEEE Conference on Decision and Control, Atlanta, Georgia, USA:
Presentation of paper “Parametric Frequency Domain Identification of a
Time-Varying System as a Time-dependent Weighted Sum of Time-
Invariant Systems”

* Lieve LAUWERS
01/09/2010 03/09/2010 Participating at the 13th IMEKO TC1-TC7 Joint Symposium, “Without
Measurement No Science”

28/10/2010 29/10/2010 Participating at the IUAP/PAI DYSCO workshop, Louvain-la-Neuve,
Château-Ferme de Profondval

* Zhi LI
30/10/2010 06/11/2010 2010 IEEE Nuclear Science Symposium and Medical Imaging
Conference , 2010- Knoxville, Tennessee, USA: Presentation of paper
“Nonlinear least-squares modeling of 3D interaction position in a
monolithic scintillator block”

* Ebrahim LOUARROUDI
28/10/2010 29/10/2010 Participating at the IUAP/PAI DYSCO workshop, Louvain-la-Neuve,
Château-Ferme de Profondval

30/03/2010 01/04/2010 29th Benelux Meeting on System and Control, Heeze, The Netherlands:
Presentation of paper: “Identification of Linear, Periodically Time-Varying
Systems”

31/05/2010 31/05/2010 Participating at the IUAP/PAI DYSCO Study day, Gent, het Pand

Frequency Domain Estimator for Linear, Periodically Time-Varying
Systems”

* Anna MARCONATO
30/03/2010 01/04/2010 29th Benelux Meeting on System and Control, Heeze, The Netherlands:
Presentation of paper: “Estimating nonlinear dynamics in nonlinear
state-space models”

31/05/2010 31/05/2010 IUAP/PAI DYSCO Study day, Gent, het Pand,: Presentation of poster
“Estimating nonlinear dynamics in nonlinear state-space models

06/09/2010 12/09/2010 UKACC International Conference on CONTROL 2010, Coventry, UK:
Presentation of paper “A simple and fast technique to evaluate the
possibility of approximating a nonlinear system by a nonlinear PISPO
model”

nonlinear dynamics in nonlinear state-space models”
• Griet MONTEYNE
30/03/2010 01/04/2010 29th Benelux Meeting on System and Control, Heeze, The Netherlands: presentation of paper: "Behavioral modeling of the thermal dynamics of borefields for geothermal applications"
31/05/2010 31/05/2010 Participating at the IUAP/PAI DYSCO Study day, Gent, het Pand
28/10/2010 29/10/2010 Participating at the IUAP/PAI DYSCO workshop, Louvain-la-Neuve, Château-Ferme de Profondval

• Rik PINTELOM
30/03/2010 01/04/2010 Participating at the 29th Benelux Meeting on System and Control, Heeze, The Netherlands: Chairman session "System Identification C"
01/05/2010 06/05/2010 I*MTC 2010, International Instrumentation and Measurement Technology Conference, Austin, Texas: Presentation of paper "Noise Leakage Suppression in FRF Measurements Using Periodic Signals"
31/05/2010 31/05/2010 Participating at the IUAP/PAI DYSCO Study day, Gent, het Pand
28/10/2010 29/10/2010 Participating at the IUAP/PAI DYSCO workshop, Louvain-la-Neuve, Château-Ferme de Profondval

• David RIJLAARSDAM
10/04/2010 13/04/2010 ASPE 2010, Spring Topical Meeting in Cambridge, Massachusetts, USA: Presentation of paper "Frequency Domain Based Feed Forward Tuning for Friction Compensation"

• Yves ROLAIN
22/05/2010 30/05/2010 IEEE MTT-S Symposium, Annaheim, California: Presentation of paper "A VNA based broadband loadpull for non-parametric 2-port Best Linear Approximation Modelling"

• Johan SCHOUKENS
05/03/2010 05/03/2010 Université de Compiègne, France: Visit Prof. Antoni Jérome, member of PhD committee Erlian Zhang
30/03/2010 01/04/2010 Participating at the 29th Benelux Meeting on System and Control, Heeze, The Netherlands: Chairman session "System Identification B"
01/05/2010 06/05/2010 I*MTC 2010, International Instrumentation and Measurement Technology Conference, Austin, Texas: Presentation of paper "Design of excitation signals for nonparametric measurements on MIMO-systems in the presence of nonlinear distortions"

05/11/2010 05/11/2010 Muted lecture Faculté Polytechnique de Lausanne (FPL), Switzerland

14/12/2010 20/12/2010 49th IEEE Conference on Decision and Control, Atlanta, Georgia, USA: Presentation of paper "On the Use of Parametric and Non-Parametric Noise-models in time- and frequency domain System Identification"

- Maarten SCHOUKENS
  28/10/2010 29/10/2010 IUAP/PAI DYSCO workshop, Louvain-la-Neuve, Château-Ferme de Profondval: Presentation of poster "Parametric identification of parallel Hammerstein and parallel Wiener systems"

- Jonas SJOBERG
  31/05/2010 31/05/2010 Participating at the IUAP/PAI DYSCO Study day, Gent, het Pand

- Diana UGRYUMOVA
  28/10/2010 29/10/2010 IUAP/PAI DYSCO workshop, Louvain-la-Neuve, Château-Ferme de Profondval: Presentation of poster "Modeling and identification of distillation columns using optimized excitations"

- Leo VAN BIESEN
  21/03/2010 23/03/2010 Institut Supérieur de l'Aéronautique et de l'Espace - Toulouse, France: Visit at SUPAERO in the frame of agreement around bidiplomering
  27/05/2010 03/06/2010 TEMPMEKO & ISHM 2010, Portorož, Slovenia: Participating at the IMEKO board meetings, General Council and the conference
  31/08/2010 05/09/2010 Participating at the workshop in Kinshasa in the frame of the VLIR-EI project (ISTA - RDC)
  08/09/2010 10/09/2010 Participating at the IMEKO TC4-TC19 Symposium "Instrumentation for the Information and Communication Technology Era", Kosice, Slovakia
  18/09/2010 26/09/2010 University Burundi, formation in the frame of VLIR-IUS project: participating as a project leader

- Wendy VAN MOER
  30/03/2010 01/04/2010 Participating at the 29th Benelux Meeting on System and Control, Heeze, The Netherlands
  01/05/2010 06/05/2010 I'MTC 2010, International Instrumentation and Measurement Technology Conference, Austin, Texas: Presentation of paper "Compensating out-of-band nonlinear distortions"
  31/05/2010 31/05/2010 IUAP/PAI DYSCO Study day, Gent, het Pand: Presentation of poster "Linearizing oscillometric blood pressure measurements: (non)sense?"
  17/08/2010 20/08/2010 University of Gavle, Sweden: Meeting concerning cotutelle-agreements
  28/10/2010 29/10/2010 Participating at IUAP/PAI DYSCO workshop, Louvain-la-Neuve, Château-Ferme de Profondval
• Anne VAN MULDERS
  30/03/2010 01/04/2010 29th Benelux Meeting on System and Control, Heeze, The Netherlands: Presentation of paper: "Reduction of polynomial nonlinear state-space models by means of nonlinear similarity transforms"
  31/05/2010 31/05/2010 IUAP/PAI DYSCO Study day, Gent, het Pand,: Presentation of poster “Reduction of polynomial nonlinear state-space models”

• Laurent VANBEYLEN
  30/03/2010 01/04/2010 29th Benelux Meeting on System and Control, Heeze, The Netherlands: Presentation of paper: "Estimation of the probability of stable operation over a given time interval for discrete-time nonlinear state-space models"
  31/05/2010 31/05/2010 Participating at the IUAP/PAI DYSCO Study day, Gent, het Pand

• Gerd VANDERSTEEN
  01/05/2010 06/05/2010 I^MTC 2010, International Instrumentation and Measurement Technology Conference, Austin, Texas: Tutorial presentations “Nonlinear Distortion Analysis in Circuits and Systems” and “DSP in Measurement, Part 2, convolution / correlation”
  29/05/2010 02/06/2010 ISCAS 2010, Paris, France: Presentation of tutorial "Nonlinear distortion analysis of circuits and systems"
  28/10/2010 29/10/2010 Participating at IUAP/PAI DYSCO workshop, Louvain-la-Neuve, Château-Ferme de Profondval

• Dhammika WIDANAGE
  01/02/2010 04/02/2010 IMAC-XXVIII conference, Jacksonville, Florida USA: Presentation of paper "Assigning the Nonlinear Distortions of a Two-input Single-output System"
  28/10/2010 29/10/2010 IUAP/PAI DYSCO workshop, Louvain-la-Neuve, Château-Ferme de Profondval: Presentation of poster "Nonparametric modelling of a linear time varying system"
1.5 ORGANISATION CHART OF DEPARTMENT ELEC

Team A: Automatic Measurement Systems, Telecommunications and Laboratory of Underwater Acoustics
Prof. Dr. ir. Leo VAN BIESEN, full-time professor
Dr. Musa BISHARA (until August 2010)
BSc. Hernan CORDOVA, PhD student
Ir. Wim FOUBERT, PhD scholarship
Ir. Carine NEUS, research assistant
Dr. Indira NOLIVOS ALVAREZ (until October 2010)

Team B: System Identification & Parameter Estimation of Linear and Nonlinear Systems
Prof. Dr. ir. Johan SCHOUKENS, full-time professor
Dr. ir. Michel GEVERS, Professor emeritus (since October 2010)
Ir. John LATTAIRE, PhD scholarship
Ir. Ebrahim LOUMAROUFI, PhD scholarship
Dr. ir. Anna Marconato, Post doc.
MSc. David OLIVE UNBE, PhD scholarship (since 1/1/11)
Prof. Dr. ir. Rik PINTELON, full-time professor
Dr. ir. Jonatas TROPE, Post doc. (until June 2010)
Ir. Koen TIELS, PhD scholarship (since Sept. 2010)
Ir. Laurent VANBEYLVEN, research assistant
Ir. Mattja VAN DE WALLE, PhD scholarship
Ir. Anne VAN MULDERS, PhD scholarship
Prof. Dr. David WESTWICK, post-doc (since 1/1/11)
Dr. DHamilla WIDANAGE, Post doc.

Team C: Applied Signal Processing for Engineering (ASPE)
Prof. Dr. ir. Gerd Vandersteen
Prof. Dr. ir. Alain BAREL, Professor emeritus
Ir. Lynn BOS, PhD scholarship, PhD student
MSc. M. EL-BAROUKY, PhD student
Ir. Diane DE COSTER, PhD student (since October 2010)
Dr. ir. Ludwig DE LOCHT, Post Doc
Ir. Liesbeth GOMMÉ, PhD scholarship
MSc. Maurik JAIN, PhD student (since Sept. 2010)
MSc. Zhi LI, PhD scholarship
Ir. Greet MONTENYE, PhD scholarship
Prof. Dr. ir. Yves ROJAIN, full-time professor
Ir. Mirko SCHOLZ, PhD Student IMEC
Ir. Maarten SCHOUKENS, PhD student (since August 2010)
Ir. Diana UGRYUMOVA, PhD student (since May 2010)
Dr. Koen VANDERMIOT (until September 2010)

Head of the Department ELEC
Prof. Dr. ir. Johan SCHOUKENS

Technical and Administrative Staff:
ing. Wim DELCOURTE, industrial engineer
(20% Staff ELEC, 80% Staff Faculty IR)
BSc. Lorena GASSIOUM, part-time secretary
(until June 2010, Methusalem)
Mrs. Jenny LIEVENS, part-time secretary
Mr. Johan PATTYN, technician
MSc. Ann PINTELON, 4/5 administrative coordinator (Methusalem)
ing. Sven REYNERS, network manager
(Methusalem)
Mr. Jean-Pierre WEVERS, technician (until
June 2010)

Team E: Identification of Biochemical Signals Systems
MSc. Maëtte BAUWENS, PhD student
MSc. Veerle BEELAERTS, PhD student

Team D: Medical Measurements and Signal Analysis (MEESA)
Prof. Dr. ir. Wendy Van Moer
Dr. Kurt BARE, Post doc.
Ir. Per LANDIN, PhD student, cotutelle
(since 1/2/2011)
Ir. Lieve LAUWERS, research assistant
Ir. Charles NADE, PhD student, cotutelle agreement
(since September 2010)
Ir. Oscar J. OLARTE RODRIGUEZ (since Nov. 2010)
Bsc. Kevin VOET, PhD student (since Aug. 2010)
1.6 FUNCTIONAL ORGANISATION OF THE DEPT. ELEC

Head of department ELEC
J. Schouwens

Technical assistance
- Electronic Design assistance
  J. Pattyn
  W. Delcourt
- Mechanical Design assistance
  J. Pattyn
- Didactical Design assistance
  J. Pattyn
- Purchase Electronic Components
  J. Pattyn
- Purchase General Components
  J. Pattyn
- Instrument Maintenance Coord.
  W. Delcourt
- Instrument Inventory & Loan serv.
  W. Delcourt
- Office/ Lab. accommodation
  J. Pattyn

Administration
- Centralization
- Correspondence
- Personnel files
- Copy cards
- Thesis printouts
- Administration
- Purchases
- Contracts
- Office material stock
- General secretariat
- Accounting

Infocenter
- Instrument and accessory overview
  J. Pattyn
- Library
- Magazine overview
- Literature overview
- Spare manuals
- Thesis books
- Data books
- Course notes
- Lab. Notes
- Internal notes
- Publication list
- Annual Report

Research Organization
- Coordination
  Thesis/PhD follow-up
  Industrial contacts
  Staff follow-up
  L. Van Biesen - team A
  J. Schouwens - team B
  G. Vandersteen - team C
  W. Van Moer - team D
  J. Schoukens - team E
  Research work
  Research staff

Support to other bodies, internal or external to the VUB
- AUTOMATICA - IFAC
  J. Schouwens, associate editor
  A. Pintelon, administration, follow-up
- IEEE Instrumentation & Measurement Society, Adcom
  R. Pintelon, K. Barbé, G. Vandersteen, W. Van Moer
  associate editors
- IEEE Microwave Theory and Techniques
  associate editor: W. Van Moer
- IMEKO:
  L. Van Biesen, President, Liaison Officer to IEEE
  IMEKO General Council: L. Van Biesen, Chairman
  IMEKO Technical Board: L. Van Biesen, member
  IMEKO Editorial Board: L. Van Biesen, member
- ELSEVIER - IMEKO Journal “Measurement”
  L. Van Biesen, associate editor
- Faculty of Electrical Engineering
  J. Schouwens, vice-chairman of Research and investment council
  J. Schoukens: member board faculty
  L. Van Biesen, Chairman Council Bachelor Studies
  R. Pintelon, chairman PhD council
  Y. Reijnders, chairman IT council
  W. Delcourt, support of system administrator
  W. Van Moer, chairman doctoral school NSE, Secretary ORE
- The Royal Academies of Science and the Arts of Belgium
  Member of National Committee of Radio-Electricity:
  L. Van Biesen
- Vrije Universiteit Brussel
  J. Schoukens, member research board
  J. Schoukens, member research board (OZR)
  J. Schoukens, member of Senate
- VUB-ORBAM faculty educational council for Bachelor in Engineering Science studies
  L. Van Biesen; chairman

Computer Support
- PC workstations ELEC
  J. Pattyn
  S. Reigniers
- Support network ELEC
  J. Pattyn
  S. Reigniers

Personnel
- Job students
- Follow-up
- Fellowships
- Research contracts
- contract renewal
- visiting researchers/professors

Public Relations
- Annual Report
- Internet - ELEC home page

National/international contacts
- Organisation of workshops, conferences, ...
  Research staff
  A. Pintelon
1.7 LIST OF THE MOST IMPORTANT MEASUREMENT EQUIPMENT

1.7.1 Signal Generators

- HP E1445A VXI Arbitrary Waveform Generator, $f_{\text{max}} < 40$ MHz (3x)
- HP E1340A VXI Arbitrary Waveform Generator, $f_{\text{max}} < 42$ MHz (3x)
- Synthesizer/Function Generator, Agilent 33120A (2x)
- NI 5411 AWG
- Noise Source, HP 346B, 10 MHz-18 GHz
- Agilent, 4142B, DC power supply
- HP E1434A VXI Arbitrary Waveform Generator, 4 channel source, $f_{\text{max}}$: 65 KHz
- HP, Signal Generator, HP 83650B, 45 MHz - 40 GHz
- Tektronix, AWG710, 4 GHz
- Tektronix AWG 7052, 5GHz Arbitrary Waveform Generator
- Rhode & Schwarz, Vector Signal Generator, SMIQ06B, 300 kHz - 6.46 GHz
- Agilent 33250A, NI 5411
- Agilent 81101A, Pulse generator, 50MHz

1.7.2 Spectrum Analysers, Impedance Analysers, Network Analysers

- 2 channel Dynamic Signal Analyser, HP 3562, 100 kHz (2x)
- Impedance Analyser, HP 4192A, 5 Hz - 13 MHz
- Vector Impedance Meter, HP 4193 A, 0.4 - 110 MHz
- Spectrum Analyser, R&S FSU, 20 Hz- 67 GHz
- µwave Network analyser, E8364B, 10 MHz - 50 GHz
- µwave Network analyser, N5242A, 10 MHz – 26.5 GHz 4 port
- Noise Gain Analyser, Eaton 2075 B, 10 MHz - 1800 MHz
- Network Analyser, HP 8753 C, 300 kHz - 6 GHz
- Spectrum Analyser, HP 8565 E, 9 kHz - 50 GHz
- PNA Network Analyser, Agilent, 5 0MHz - 50 GHz
- Impedance Analyzer, Agilent E4991A, 10MHz - 3GHz

1.7.3 Digitizers

- 4 channel digitizer, Nicolet 490, 200 MHz, 8/12 bit
- 4 channel Digital Sampling oscilloscope, HP 54120T, 20 GHz, 11 bit
- 1 channel, HP E1430A VXI ADC 10 MHz, 16 bit (10x)
- 1 channel, HP E1437A VXI ADC 20 MHz, 16 bit (4x)
- 2 channel, HP E1429B VXI ADC 20 MHz, 12 bit (2x)
- 8 channel, HP E1433A VXI ADC 196 KHz
- 2 NI 5911 flexres digitizer
• TDS 3032 digital phosphor oscilloscope
• 2 NI Elvis II

1.7.4 Miscellaneous

• Dual programmable filter, DiFa PDF 3700, 100 kHz
• Dual adjustable filter, Wavetek, 100 kHz
• Logic state analyser HP 1645A
• µwave power meter, HP436A, 10 MHz-18 GHz
• 4 VXI racks +4 MXI controllers + Digital cards
  (2x Agilent E4841A + 1 Agilent E4805A)
• HP E1450, VXI timing module
• HP E1446A, VXI power module generator
• Wafer Probe Station
• Polytec Optical Fibre Vibrometer
  Velocity range (Doppler interferometer): 1, 5, 25, 125, 1000 mm/s/V
  Displacement range (Fringe Counter): 2, 8, 20, 80, 320, 1280, 5120 µm/V
• 2 PXI mainframes + MXI controller + embedded controller
• Custom-built measurement setup for making geo-referenced GSM network measurements
• 4 hTC P3600 smart phones (equipped with 2G, 3G, Bluetooth, WiFi and GPS)
• 2 JRC DGPS 200

1.7.5 Underwater Acoustics

• Raytheon V860 echosounder
• B&K hydrophones, amplifiers etc.
• Panametrics transducers (500 kHz, 1MHz)
• D-GP5 Beacon Receiver KODEN (KBR-90)
• 2 watertanks + positioning system
• Anritsu BTS Master MT8222A, High Performance, Handheld Base Station Analyzer
# 1.8 FINANCIAL SUPPORT 2009

<table>
<thead>
<tr>
<th>Sponsor (project leader)</th>
<th>Duration project</th>
<th>Activity</th>
<th>Approx. amount (in €)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DWTC232 (R. Pintelon)</td>
<td>2007-2011</td>
<td>Dynamical systems, control and optimization (DYSCO)</td>
<td>400000</td>
</tr>
<tr>
<td>IWT419 (J. Schoukens)</td>
<td>2009-2013</td>
<td>LeCoPro Learning Control for Production Machines</td>
<td>76491</td>
</tr>
<tr>
<td>FWOAL420 (L. Van Biesen)</td>
<td>2007-2010</td>
<td>Design and evaluation of DSL systems, with exploitation of common mode signals</td>
<td>196600</td>
</tr>
<tr>
<td>FWOAL434 (y. Rolain)</td>
<td>2008-2011</td>
<td>Scalable compact macromodels for general microwave and RF structures</td>
<td>138800</td>
</tr>
<tr>
<td>FWOAL454 (J. Schoukens)</td>
<td>2008-2011</td>
<td>Iteratief leren van model en regelaar voor sterk niet-lineaire systemen</td>
<td>277600</td>
</tr>
<tr>
<td>FWOAL483 (G. Vandersteen)</td>
<td>2008-2011</td>
<td>Analysis, modeling and design of multi-rate discrete-time sigma-delta circuits</td>
<td>23280</td>
</tr>
<tr>
<td>FWOAL561 (G. Vandersteen)</td>
<td>2010-2013</td>
<td>Black box modeling of boreholes for MPC of ground-coupled heat pumps</td>
<td>160000</td>
</tr>
<tr>
<td>FWOTM420 (Y. Rolain)</td>
<td>2007-2010</td>
<td>Advanced calibration and Instrumentation setups for nonlinear RF devices, bench fee PhD Liesbeth Gommé</td>
<td>14880</td>
</tr>
<tr>
<td>FWOTM423 (R. Pintelon)</td>
<td>2007-2011</td>
<td>Measurement and modeling of weakly nonlinear slowly time-varying systems, bench fee PhD John Lataire</td>
<td>14880</td>
</tr>
<tr>
<td>FWOTM445 (W. Van Moer)</td>
<td>2007-2013</td>
<td>Identification of multiport nonlinear microwave systems, bench fee post-doc. Wendy Van Moer</td>
<td>12000</td>
</tr>
<tr>
<td>FWOTM449 (A. Debrauwere)</td>
<td>2007-2010</td>
<td>Quantification and understanding of biologically mediated oceanic carbon export from the upper ocean and through the water column, using a multidisciplinary approach, bench fee post-doc. A. Debrauwere</td>
<td>12000</td>
</tr>
<tr>
<td>FWOTM562 (K. Barbé)</td>
<td>2010-2013</td>
<td>System Identification of Finite Records, bench fee post-doc Kurt Barbé</td>
<td>12000</td>
</tr>
<tr>
<td>HERC3 (W. Van Moer)</td>
<td>2008-2013</td>
<td>Multidisciplinary centre for measurements using advanced technologies of the Brussels University Association</td>
<td>78418</td>
</tr>
<tr>
<td>HOAI3 (R. Pintelon)</td>
<td>2007-2011</td>
<td>Een geïntegreerd systeem voor het opmeten en modelleren van elektrochemische reacties: een nodige voorwaarde voor het vergaren van betrouwbare data</td>
<td>17500</td>
</tr>
<tr>
<td>IWT410 (L. Van Biesen)</td>
<td>2008-2010</td>
<td>ISEED-Innovation on stability, spectral and energy efficiency in DSL</td>
<td>170884</td>
</tr>
<tr>
<td>IWT419 (J. Schoukens)</td>
<td>2009-2013</td>
<td>LeCoPro Learning Control for Production Machines</td>
<td>14609</td>
</tr>
<tr>
<td>Legal Expertise (L. Van Biesen)</td>
<td>Since 1995</td>
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### 1.9 AWARDS

#### 1.9.1 Grade of Fellow (IEEE)

The Institute of Electrical and Electronic Engineers, Inc. elected the grade of fellow to:

- **Johan Schoukens**: for contributions to frequency domain system identification and the integration of measurement, signal processing and estimation theory (1997)
- **Rik Pintelon**: for fundamental research in frequency domain system identification and its applications in instrumentation, control and signal processing (1998)
- **Yves Rolain**: for contributions to measurement and modeling of nonlinear microwave devices (2005)
1.9.2 Belgian Francqui Chair ULB - 2006-2007

Prof. Dr. ir. Johan Schoukens: “Identification of linear systems in the presence of nonlinear distortions: a frequency domain approach”

Linear models are at the basis of many engineering activities. The aim of this course is to identify these models from experimental data. In real life, nonlinear distortions violate the ideal linear framework. Two solutions are discussed to extend the classic linear modelling approach. First the linear framework will be extended to include these distortions using best linear approximations and nonlinear noise sources. Alternatively, the nonlinear distortions will be explicitly modelled.

Lectures (see pdf-files at http://wwwtw.vub.ac.be/elec/ELECcourse.htm):

- Inaugural: System Identification from data to model
- Lesson 1: Frequency Response Function Measurements
- Lesson 2: Impact of Nonlinear Distortions on the Linear Framework
- Lesson 3: System Identification (pdf-file)
- Lesson 4: Identification of Linear Systems
- Lesson 5: Identification of Nonlinear Systems

1.9.3 Awards granted by the VUB, on the proposition of the department ELEC

- Title of Doctor Honoris Causa to Prof. P. Eykhoff (Technische Universiteit Eindhoven) on April 4, 1990 (VUB, Brussels)
- Medal of Excellence to William Hewlett and David Packard on March 3, 1995 (VUB, Brussels)
- Medal of Excellence to Joseph F. Keithley on June 4, 1996 (Gothic Town Hall of Brussels)
- Title of Doctor Honoris Causa to Prof. M. Gevers (Université Catholique de Louvain - CESAME) on November 28, 2001 (VUB, Brussels)

1.9.4 Distinguished Service Award from IMEKO

The International Measurement Confederation extends to Prof. Leo Van Biesen this Distinguished Service Award:

- As recognition and appreciation for his valuable contributrition to the international exchange of scientific and technical information relating to developments in measuring techniques, instrument design and manufacture and in the application of instrumentation in scientific research and in industry.
- For his continuous support in IMEKO as member of several TCs, delegate of the Belgian Member Organization to the General Council, President Elect and Chairman of the Technical Board from 2000 to 2003, President of the Confederation from 2003 to 2006 and Past President and Chairman of the Advisory Board from 2006 to 2009.

1.9.5 Doctor Honoris Causa

Prof. Em. Ronny Van Loon received the title of “Doctor Honoris Causa” from the Hanoi University of Technology, in October 2008, for his personal contributions to the VLIR HUT IUC program in
particular and the development of Hanoi University of Technology in general over the past 10 years. Thanks to his tremendous efforts as a key promoter since the establishment in 1998, the VLIR IUC programs with HUT has vigorously developed and reaped fruitful achievements, significantly contributing to the expansion of international network and international academic exchange at Hanoi University of Technology.

1.9.6 Member of the “Royal Flemish Academy Of Belgium For Science And The Arts”

Prof. Dr. ir. Johan Schoukens has been elected in December 2009 as member of the “Royal Flemish Academy Of Belgium For Science And The Arts” for the section “Technical Sciences”.

1.9.7 Paper awards (2009)

Mussa Bshara and Leo Van Biesen received the “Top Six Achievement Award “Winning Paper” for the paper “Potential Effects of Power Line Communication on xDSL Inside the Home Environment” presented at the VIII Semetro. 8th International Seminar on Electrical Metrology João Pessoas, Paraiba, Brazil June 17 - 19, 2009


Mussa Bshara and Leo Van Biesen received the “Best Paper Award” for the paper “Fingerprinting-based Localization in WiMAX networks depending on SCORE measurements”, presented at the Fifth Advanced International Conference on Telecommunications, AICT 2009, Venice/Mestre, Italy, May 24-28, 2009
2. Short Description of the Research Projects/ Team

2.1 TEAM A: AUTOMATIC MEASUREMENT SYSTEMS, TELECOMMUNICATIONS AND LABORATORY OF UNDERWATER ACOUSTICS

2.1.1 Introduction to Team A

The activities of team A directly related to fundamental electricity, deal with the set-up of computer controlled measurement systems, the design of new intelligent instruments, the processing of the measured data (DSP and algorithmic treatment) and the implementation of A.I.- techniques in instruments for the automatic interpretation of the acquired measurements. The technical applications areas are quite diverse and cover areas in the field of electrical and electronic systems, but a lot of special care is also given to earth science applications.

This team is also active in telecommunication projects and studies, which deal with voice coded transmissions (telephony) and with robust coded digital transmission (ADSL, VDSL). Communication channels are modelled, with emphasis on the physical layer.

Moreover, in the field of underwater acoustics important research projects are developed since 1985. Fundamental as well as applied research is carried out in the field of the modelling of marine systems, marine acoustics, sub bottom profiling and sediment classification.

Prof. Dr. ir. L. Van Biesen has been the Belgian delegate in the board of IMEKO since 1993 and chairman of the Technical Committee TC-7 on Measurement Science since 1994, up to 2000, has been vice-chairman of the Technical Committee TC-19 on Environmental Measurements since 1999, President-Elect of IMEKO (2000-2003) and was the President of IMEKO (2003-2006), and has been Post-President of IMEKO (2006-2009)

2.1.2 Short Description of the Research Projects of Team A

2.1.2.1 Design and evaluation of Multiple-Input-Multiple-Output channel models for DSL systems
(Wim Foubert, Leo Van Biesen)

Digital Subscriber Line (DSL) technology provides broadband service over ‘twisted pair’ copper wires of the existing telephone network. Current DSL systems make only use of differential mode (DM) signals, which refers to the electrical voltage difference between the two wires of a twisted pair (see Figure 1). However, in most countries there are two twisted pairs that enter each house.
In next generation DSL technologies, all four wires will be exploited. In this way, two differential mode signals and an additional phantom mode signal can be defined. This new signal is the voltage difference between the references of each twisted pair. In the differential mode, the currents in the two conductors of the twisted pair are in opposite direction. In the phantom mode, they are in the same direction and another twisted pair stands in for the return path. In this way, the phantom mode signal is invisible for the differential mode signal on each pair. The phantom mode signal can also be seen as a differential mode signal but now one uses four conductors instead of two. Using also the phantom mode signal in addition to the differential mode signal, the capacity can be three times higher than the conventional differential mode only capacity!

In order to use also the phantom mode signal, we need reliable transmission line models which take also this signal into account. The derivation of the new models is based on the multiconductor transmission lines (MTL) theory. This theory is only valid for uniform line segments. Figure 2 shows how the behavior of a twisted pair can be approximated. The representation contains a resistor $R$, an inductor $L$, a conductance $G$ and a capacitance $C$. For our model, good approximations for the different physical parameters are indispensable.

This problem is decoupled. First we consider the transversal plane to determine the resistance $R$ and the inductance $L$. Therefore we use a quasi-stationary approximation since the diameter of the quad is much lower than the wavelengths of the transported signals. An analytical expression exists for the transversal plane, which is called the series impedance and was derived by Belevitch [1]. Beside the skin effect, also the proximity effect is taken into account. This series impedance has been validated with measurements as described in [2]. In the longitudinal plane, the considered line lengths are of the same order of the wavelength. A numerical approximation technique will be used to obtain accurate results for the capacitance matrix. Also this matrix has been validated. Therefore a two-dimensional simulator, called Maxwell is used.

Once we have the complete model for a homogeneous quad, twisting will be introduced. The multiconductor transmission lines theory is only valid for uniform line segments. But, if we want to allow wire twists, strands and variations our cable is not uniform at all. To overcome this problem, the system will be split up in very short line segments. Each segment is considered to be uniform and is represented by a transmission matrix. The overall cable description is obtained by multiplication of the different matrices. In this way, it’s easy to increase the number of pairs, change the twist rate, stranding or isolation just by changing one or more parameters in the model.
In the next part, the eigenmodes of the quad are investigated. Since we know the four parameters (R, L, G and C), it is possible to calculate the product YZ where Y represents the admittance matrix and Z is the impedance matrix. Diagonalizing this product gives four eigenvalues and the corresponding eigenvectors. Analyzing this, we notice that the two differential modes and the phantom mode are all eigenmodes of the system. Moreover there is no crosstalk between the different modes. This proves that exploiting also the phantom mode signal will strongly increase the available capacity.

References


2.1.2.2 Binder identification of DSL lines with reflectometric measurements
(Carine Neus, Wim Foubert, Leo Van Biesen, Yves Rolain, Patrick Boets*, and Jochen Maes*)

(*) Bell labs Antwerp, Alcatel-Lucent

The twisted pairs of a telephone network are grouped into binders, e.g. 20 pairs or more can be grouped in one binder, as shown in Figure 3. When several digital subscriber line (DSL) services with overlapping frequency bands operate on these twisted pairs, the presence of crosstalk will limit the total performance. This is especially an issue for the latest xDSL technologies (e.g. VDSL2). For this reason, Dynamic Spectrum Management proposes to coordinate the signals travelling on the different lines in an intelligent way. However, this technique requires that the operators know which twisted pairs are situated in the same binder. Knowledge about the structure of the binder network and the distribution of the pairs over the binders can also be useful for other purposes, e.g. diagnosis. For example, if a fault is detected on one twisted pair, it might be worth testing whether the other twisted pairs in the same binder experience similar problems.

We have developed a technique to identify if two twisted pairs are located in the same binder or not [3]. As the twisted pairs may share the same binder for a certain distance only (see Figure 4), the method is also extended to find the distance over which they coexist. The measurement technique relies on measurements from one end of the line only (single ended measurements). The main advantage is that this allows automation of the binder identification, as all measurements are performed from the central office, without requiring interaction at the customer premises. The implementation of an automated algorithm is left for future work; instead, the emphasis is put on
the measurement setup and on the proof of concept, as such opening the way to many applications based on the use of binder related information. In the final implementation, the aim would be to implement this testing functionality into the xDSL modems, which are equipped with standardized single ended line test capability.

Reference

2.1.2.3 A Bayesian Model To Construct A Knowledge Based Spatial Decision Support System For The Chaguana River Basin (Indira Nolivos Alvarez, Leo Van Biesen)

Expert systems and GIS in combination with data and numerical models can facilitate the construction of spatial decision support systems in problem domains where knowledge is available but data are limited. In turn, a knowledge based decision support tool can reduce the complexity of decision-making in water resources management (IWRM) by providing decision makers with an easy access to up-to-date information, analysis tools and uncertainty assessment. The research goal is to provide water managers with a computational tool for decision support that combines different information sources to structure the available knowledge on a water management problem and to explore possible management alternatives for an Ecuadorian river basin.

Figure 4 Two twisted pairs sharing a first common binder and subsequently splitting into different binders.

Figure 5 Architectural design of the spatial decision support system
The spatial decision support system (SDSS) has been designed in a modular architecture including as major components: a graphical user interface (GUI), an expert model and a data repository which encloses the knowledge and data bases within the system (see figure 1). The data repository relates the data and knowledge bases (i.e. MySQL, PostgreSQL) with the geo referenced objects (i.e. point, line and polygons) and the expert models embedded in the system. Currently, users can consult spatial information, create and set up different expert models, run the inferences, view and compare results from different scenarios using a web browser by selecting areas (i.e. polygonal selection), clicking and typing.

The Bayesian Network technique has been applied for the construction of the expert model. The focus is on the economic incentives that banana farmers have to apply pesticides on their plantations. The problem is formulated as a representative banana farm model, in which the most relevant production factors are considered and represented graphically as causal variables of banana production. The spatial heterogeneity is addressed by setting up the model parameters based on the differences in farm management behaviour per sub-basin, for all sub-basins of the Chaguana river basin in which banana production is the main land use.

Figure 6 Bayesian Network model for the Chaguana river basin.

Figure 6 shows the expert model that has been developed for the water quality problem inside the Chaguana river basin, where the objective variables are banana production and Propiconazole concentration at outlet. The expert model has been constructed, parameterized and validated using expert knowledge, local information (i.e. datasets and agriculturist practices collected from several banana farms inside the Chaguana river basin), and the predictions for the concentration of the fungicide Propiconazole at the outlet provided by the AGNPS model for different Propiconazole application scenarios to control black Sigatoka in banana plantations, under normal weather conditions (i.e. considering the seasonal variation effect only).
The banana production model has proved good performance, when tested under different weather and agriculturist management conditions and can provide decision makers with the expected probability of occurrence of good banana production under certain conditions. On the other hand, the Bayesian Network representation of the water quality component provides decision makers with information about the expected probability of occurrence of high Propiconazole concentration at outlet (once the fungicide is released over the banana farms and washed into the rivers) for different weather conditions, application schedules and Propiconazole retention capacity.

It is believed that water managers for the Chaguana river basin will take more effective actions to control water pollution, once they are better informed about the economical and environmental implications of their choices.

2.2 TEAM B: SYSTEM IDENTIFICATION AND PARAMETER ESTIMATION

2.2.1 Introduction to Team B

The main interest of the identification team is situated in the development of new identification methods and their application to real life problems. The team is involved with many aspects of the identification theory:

- experiment design
- development of estimators
- modelling problems

The identification of linear and nonlinear systems is studied.

Throughout our work we make the following choices:

- use of periodic excitations whenever it is possible, use random excitations if it is imposed by the user.
- use of non parametric noise models to characterize the stochastic disturbances
- use of an errors-in-variables framework: all measured signals are assumed to be disturbed by noise.
- believe your data, not your prejudices

It will not always be possible to act along these clear principles, but whenever we face a choice, they are an important factor in our decision process.

Another important aspect of our general approach is that we start the process by gathering system knowledge from the measurements. This gives in a very early phase of the identification process an idea of the global complexity of the modelling problem. For the linear systems this phase boils down to the non parametric measurement of the frequency response function, which is usually of a high quality due to the periodic excitation approach. It contains a lot of information about the system. For nonlinear systems the situation is not that clear, and a number of ideas are under study at this moment.
IDENTIFICATION OF LINEAR SYSTEMS

In the eighties, ELiS, an estimator to identify single input single output (SISO) linear dynamic systems in the presence of uncorrelated input/output noise, was developed at the department ELEC. In a next step this estimator was generalized to multiple input/multiple output systems in the presence of correlated input and output noise.

Since linear dynamic systems are used as a basic modelling tool in a very wide range of applications, it is clear that this work has a lot of applications. We applied this modelling approach to chemical problems (traction batteries, diffusion processes), power engineering (electrical machines, power transformers; fault localisation on a cable), mechanical problems (flutter analysis, flexible robot arm) measurement area (compensation of the dynamics of an acquisition channel, modelling the dynamics of a sensor), and signal processing (design of digital filters). In all these applications the identified transfer function model was an intermediate step, for example leading to a better physical insight in the structure of the DUT, or to be used to improve the quality of the process control.

Nowadays we are further developing the estimators, making them more robust and user friendly, resulting in a wider applicability of ELiS. Moreover a lot of effort is spent to generalize frequency domain identification methods so that they also can be applied under exact the same conditions as time domain methods, but still offering the advantages of using a non parametric noise model.

**robustification:**

- what happens if the true model is not contained in the considered model class, for example when non linear distortions or unmodelled dynamics are present
- what can be done if no noise information is available
- identification of high order systems, identification of an over parametrized model
- generation of improved starting values

**user friendly:**

- is it possible to extract the noise information from the same measurements that are used to identify the system without user interaction
- is it possible to guide the inexperienced user to a good solution of his identification problem
- development of fully automated processing methods: from raw time domain data to validated models (including automatic detection and processing of the periodicity of the signals; extraction of non parametric noise models; model selection; model validation)
**generalization:**

- identification of MIMO systems: design of excitation signals, development of new algorithms, constraint estimation (stability, positive definite systems)
- identification of continuous time models using arbitrary excitations
- developing a general theoretic framework linking time and frequency domain identification
- generalization to other fields like electrochemical reactions (÷s) and microwave systems (Richardson)

**IDENTIFICATION OF NON LINEAR SYSTEMS**

In the last 10 years we started to study more intensively identification of non linear systems. It is not a good idea to define the class of models under study by a negation. Just as it is an impossible task to make a study of the zoology of the 'non elephants', it is impossible to grasp all non linear systems in one framework. We should be more specific and give a positive definition of those systems that we will consider. In this project we focus on those systems where a periodic input results in a periodic output with the same period as the input (we call it PISPot systems). This excludes a lot of phenomena like chaos, bifurcation, but it is still a wide class, including hard non linear systems like clippers, relays, deep saturation etc. Selecting a specific model structure for these system is still a very complex task. Not only the non linear behaviour should be properly characterised, also the dynamics should be captured. This requires that many choices from the user, compared to the linear problem, that it is not a good idea to start immediately with a parametric model when identifying a non linear system. Too many questions would remain unanswered. For that reason, we prefer to start with a non parametric representation of the system, trying to get a first insight in its behaviour. Only in a second step, we will eventually move to a specific parametric model that might be well adapted to the given problem, using the previously gained insights to select a dedicated model structure.

Our work on identification of non linear systems is split in two parts. In the first part we study the impact of non linear distortions on the linear identification framework. In the second part we aim at modelling the nonlinearities.

*Linear modelling in the presence of nonlinear distortions*

Linear models are successfully applied to a wide range of modelling problems although they are based on very restrictive assumptions. The real world is not linear, and hence intrinsically the theory is not applicable. However, in practice, the linear approximations are useful and offer important advantages:

- They result in useful models that give the user a lot of intuitive insight in his problem.
- Many design techniques, that can not be easily generalised to nonlinear models, are available.
Nonlinear model building is mostly difficult and time consuming, while the additional performance that is obtained might be small. So it is not obvious that the gain in model performance warrants the required efforts to build a nonlinear model.

No general framework is available for nonlinear systems as it is for linear systems. Often dedicated models are needed, complicating the development/use of general software packages.

For these reasons we work on a generalised linear framework that can be used in a nonlinear environment. Using this framework it is possible to get:

- A better understanding of the impact of nonlinear distortions on the model.
- Optimized measurement techniques that reduce the required measurement time significantly.
- Generalised uncertainty bounds that describe the model variations due to the nonlinear distortions. This allows for a better balanced design that accounts for the model limitations.
- A lower risk of being fooled by the classical linear identification methods that are widely used in commercial packages.
- Simple design rules that help to reduce the undesired impact of nonlinear distortions on practical designs.

The whole approach is based on the observation that for random excitations, a nonlinear system can be represented under very mild conditions by a linear system plus an additive noise source. The linear system \( G_R(j\omega) \) gives the best linear approximation of the output for the considered class of excitation signals, while the noise source \( \gamma_s(j\omega) \) represents all nonlinear effects that are not captured by the model.

**Identification of nonlinear systems**

Nonlinear modelling is extremely difficult. The major reason for this problem is the enormous variability that exists. Even when we zoom in to for example Volterra systems, there are still many additional degrees of freedom compared to the modelling of linear system. The only model structure question for SISO-transfer functions is the order of the numerator and denominator. For SISO-Volterra systems, the situation is much more complicated, because the model uses multiple frequency variables that can appear in any possible combination. Hence no simple prior structure selection is possible. For that reason it is our strong belief that the parametric modelling step should be preceded by a non parametric one. First the user should get an impression of the non linear behaviour, and only in the next step he can propose a parametric model structure.

For that reason we studied and still look at a number of non parametric methods like: Restoring force method, the power transfer method, the non parametric Volterra models.

For the parametric modelling we follow different approaches: non linear block-structured models and non linear state-space models

- Non linear block-structured models consists of linear dynamic blocks combined with static non linear blocks. In its most general form feedback loops can be present. The major advantage of this structure is that it still provides some physical insight in the system, and
it uses a ‘small’ number of parameters. The major disadvantage is that it is extremely hard to find good initial estimates for the individual blocks.

- Non linear state-space models cover a large class of non linear systems with a very rich behaviour. They can be considered as a potential candidate for ‘black-box’ modelling of non linear systems. The major advantage of this structure is that it is much easier to find reasonable initial estimates for the structure for systems with a dominating linear behaviour. The major disadvantage is the large number of parameters that are used. These models provide also less physical insight.

- Finally we study also dedicated non linear structures to model a number of typical high-frequency components like mixers. For these systems we use either Volterra-based descriptions, or dedicated block-structured models.

**METHUSALEM: Centre for Data Based Modelling and Model Quality Assessment**

This is a project setup by the Flemish government to give long term stability to established research groups. The project runs for 7 years, with a budget of more than 500 000 Euro/ year.

The ultimate goal of the project is to set up and maintain a centre for system identification, summarized in the motto: “From data to model”

The aim of this centre is to develop, acquire and disseminate advanced system identification methods.

**Structure of the project**

This project follows three lines towards this long term goal:

- Development of advanced identification methods for dynamic systems: Development of robust and user friendly methods for the identification of (non)linear dynamic systems. This is the home base of the identification team, and it consists of a ‘natural’ continuation and extension of the activities of the team over the last 20 years.

- High risk new challenges: Start-up of completely new high risk research lines that need a substantial development compared with the existing theory and methodology. It consists of two sub-projects:
  - Development of a ‘non-asymptotic’ identification theory: How to deal with modelling problems where the number of data points is in the same order as the number of parameters?
  - Identification in the presence of noise and model errors: Development of a new paradigm that balances/tunes noise disturbances and model errors.

- Learning, dissemination, networking: The aim is to acquire and disseminate actively knowledge from/to other fields by offering one year research grants for visitors.

- Learning: On the one hand we want to acquire system identification methods that are developed in other fields like statistics, econometrics, and are unknown within the control- and measurement society (learning), by hosting specialists of these fields for longer periods.

- Dissemination: On the other hand, many scientific disciplines face the problem of extracting mathematical models from experimental data, while this does not belong to their core business. Here, we want to give an active support to transfer sound identification
methods to these groups, by hosting and paying PhD-students of external (VUB-) groups for a longer period.

- Networking: Extend the existing international network of post-doc and senior researchers by combining short term and/or long term visits.

2.2.2 Short description of the research projects of Team B

2.2.2.1 Frequency domain identification of time-varying systems
(John Lataire and Rik Pintelon)

Frequency domain identification techniques have proven their usefulness when applied to linear, time invariant systems [2]. For particular model structures, these techniques can be extended in a straightforward fashion to the identification of linear, time-varying (LTV) systems, equally applicable to discrete-time and continuous-time systems. Examples of time-varying systems include a tower crane while raising/lowering a load or, conceptually comparable, a mass swinging at the extremity of a rod with a varying length, as illustrated in Figure 7. As the length of the rod decreases, the resonance frequency of the swinging mass increases, yielding a time-dependent dynamic behaviour of the system.

![Figure 7 Example of a time-varying system: swinging pendulum with a shortened rod, in a gravitational field.](image)

Consider the continuous-time and discrete-time LTV systems described respectively by the following differential and difference equations

\[
\sum_{n=0}^{N_c} \alpha_n(t) \frac{d^n y(t)}{dt^n} = \sum_{n=0}^{N_d} \beta_n(t) \frac{d^n u(t)}{dt^n} \\
\sum_{n=0}^{N_c} \alpha_n(t) y(t-n) = \sum_{n=0}^{N_d} \beta_n(t) u(t-n)
\]

where \( t \) is the continuous-time in the first expression, and the discrete time in the second, and \( u \) and \( y \) are the input and output signals respectively. If \( \alpha_n(t) \) and \( \beta_n(t) \) are polynomials in time, viz.:
\[ \alpha_n(t) = \alpha_{0,n} + \alpha_{1,n}t + \alpha_{2,n}t^2 + \ldots + \alpha_{N_n,n}t^{N_n}, \quad (3) \]
\[ \beta_n(t) = \beta_{0,n} + \beta_{1,n}t + \beta_{2,n}t^2 + \ldots + \beta_{N_n,n}t^{N_n}, \quad (4) \]

then model (1) can be rewritten as

\[ \sum_{n,p} \alpha_{n,p} F_d \left\{ e^{j\omega} F_d^{-1} \left\{ y(t) \right\} \right\} = \sum_{n,p} \beta_{n,p} F_d \left\{ e^{j\omega} F_d^{-1} \left\{ u(t) \right\} \right\} + I(j\omega). \quad (5) \]

with \( F_d \left\{ x \right\} \) the Discrete Fourier Transform (DFT) of \( x \), and \( F_d^{-1} \left\{ x \right\} \) its inverse. \( I(j\omega) \) can be shown to be a polynomial in \( j\omega \) (with \( \omega \) the angular frequency). This polynomial captures the errors due to windowing and sampling the signals within an arbitrary precision.

A similar transformation as given in (5) is valid for model (2), with \( j\omega \) substituted by \( e^{-j\omega t} \).

Observe that

- expression (5) is linear in the system parameters \( \alpha_{n,p} \) and \( \beta_{n,p} \), and in the coefficients of the polynomial \( I(j\omega) \). The consequence is that the minimisation of the squared equation error (which is the difference between the left and the right hand sides of (5)) can be solved analytically, and in a computationally efficient fashion.
- expression (5) is a frequency domain formulation of the ordinary differential equation (1). A frequency domain formulation allows for the construction of consistent estimators by using non-parametric models of the disturbing noise on the input and the output signals.
- very fast FFT algorithms exist to compute the regression terms in (5):
  \[ F_d \left\{ e^{j\omega} F_d^{-1} \left\{ y(t) \right\} \right\} \]
  (with \( y(t) \) replaced by \( u(t) \) and \( y(t) \)).

The outcome of this research is a simple, yet judicious estimator for linear time-varying systems, discussed in more detail in [1]. The result of this estimator applied to a time-varying electronic circuit is illustrated in Figure 8. The estimator clearly identified a filter with a time-varying resonance frequency.
Figure 8 Left: Electronic schematic of the measured system. It is a 2nd order bandpass circuit with one variable resistor. During the measurements, the value of this resistor followed a triangular waveform. Right figure: estimated evolution of the instantaneous transfer function of the circuit.

References


2.2.2.2 PARAMETERIC AND NON-PARAMETRIC FREQUENCY DOMAIN MODELING OF PERIODICALLY TIME-VARYING SYSTEMS (E. Louarroudi, R. Pintelon and J. Lataire)

It is well known that the classical Linear Time Invariant (LTI) theory provides us desirable results for many problems in daily life [1], [2]. However, in some cases the LTI (Linear Time Invariant) assumption and the related system identification techniques are not satisfied anymore, like in time-varying processes. Linear periodically time-varying (LPTV) systems could appear in a lot of engineering applications (cyclic phenomena, multi-rate sampling, speeding up LTI experiments, etc.). In this work we will capture only those systems with system properties that evolve periodically over time. A block representation of a Periodically Time-Varying (PTV) system is illustrated schematically in Figure 9. The scheduling parameters are imposed external parameters than can be controlled by the user. When a periodically scheduling parameter sequence is forced experimentally, as depicted in Figure 9, a PTV-system is created.

Parametric modeling:

Periodically time-varying systems are assumed to be well-described by linear, ordinary, continuous-time differential equations with periodically time-varying parameters:

Figure 9. Schematic block representation of a periodically time-varying system.
where $u_0(t)$ & $y_0(t) \in R$ denote respectively the undisturbed input and output signals. The periodically time-varying parameters $a_n(t) & b_n(t) \in R$ in (1) are approximated by means of finite Fourier series (idem for $b_n(t)$):

$$a_n(t) = \sum_{k=-N_a}^{N_a} A_{a,k} e^{i\Omega_n t}$$  

with $\Omega_n = \frac{2\pi}{T}$ the fundamental frequency of the system parameters.

The mean idea of this research is to identify a PTV-system using only finite unknown system parameters for the identification. Hence, the identification procedure consists of estimating the time invariant parameters $A_{a,k} & B_{a,k}$ from noisy input and output measurements in the frequency domain. The system parameters $A_{a,k} & B_{a,k}$ are tuned in such way that the deterministic part of the system matches model (1) as close as possible in least square sense.

Non-parametric modeling:

Starting from the kernel representation (or impulse response) it can be shown that a LPTV system can be modeled as an (in)finite parallel structure of weighted LTI systems. We get after truncation of the model structure in practice, say $2N_b + 1$ branches:

$$Y_0(k) = \sum_{n=-N_b}^{N_b} G_n(\omega_{k-n}) U_0(k-n)$$

where $U_0(k)$ & $Y_0(k)$ are the discrete Fourier Transform of respectively $u_0(t)$ & $y_0(t)$. The goal of this research is estimating the LTI blocks $G_n(\omega_k)$ in the frequency domain, the so-called harmonic transfer functions (HTF), in a nonparametric way embedded in an errors-in-variables framework (the input and output signals are both disturbed by noise).

The methodology, for estimation nonparametrically LPTV systems in practice, makes use of the Local Polynomial Method (LPM). The LPM is based on the fact that physical systems have a smooth behavior as function of the frequency such that they can be locally well approximated by a polynomial of low degree, typically degree 2. The method allows us to obtain high quality estimates with their corresponding uncertainty, using multi-input single-output (MISO) LTI algorithms that have been recently developed for periodic excitations [3].

References


2.2.2.3 Combining system identification and machine learning: a fast procedure for the initialization of nonlinear state-space models
(Anna Marconato, Jonas Sjöberg, Johan Schoukens)

In this work we address the problem of obtaining good starting values for the identification of nonlinear state-space models of the form:

\[ x(t+1) = f(x(t), u(t)) \]
\[ y(t) = g(x(t)) \]  

(1)

where \( u(t) \) and \( y(t) \) are the given input and output signals, \( x(t) \) is the unknown state of the system, and \( f(\cdot) \) and \( g(\cdot) \) are the nonlinear functions to be estimated.

We propose an initialization procedure that combines the use of neural networks to model the nonlinearities and classic system identification tools to capture system dynamics [1], [2], [3].

**Proposed method**

First of all, we approximate the nonlinear input-output behavior with a linear model, by estimating the best linear approximation [4]. The linear model can then be used together with the available input-output data to get an approximation of the nonlinear state \( x(t) \), so to cut the recursion loop in Eq. (1). In this way, the nonlinear functions \( f(\cdot) \) and \( g(\cdot) \) can be estimated individually as static mappings, by means of simple regression methods. Since system dynamics and nonlinearities are identified separately, we are able to test much more rapidly several possibilities for the nonlinear functions.

**Results**

Results on simulation examples show a significant improvement in terms of RMSE when adopting the proposed method. We compare the error values of the initial estimates (Figure 10) and the error values obtained when fitting all model parameters (nonlinear optimization) with (circles) and without (squares) the proposed initialization (Figure 11).

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1) and of the final fitted models (Figure 11) obtained with and without the initialization scheme, for 50 different neural network initializations.

Future work includes the application of the proposed approach on the Wiener-Hammerstein benchmark data set [5].

References:

2.2.2.4 Frequency Response Function Measurements of Multivariable Systems Using Periodic Excitation Signals
(R. Pintelon, G. Vandersteen, J. Schoukens, and Y. Rolain)

Introduction

Frequency response functions give quickly insight in the dynamical behaviour of complex systems. They are very useful for constructing and/or validating parametric transfer function model approximations of real life systems. These parametric transfer function models are then used for virtual prototyping of new products, for physical interpretation and/or better understanding of the underlying physical phenomena, for prediction and/or control, for monitoring and fault detection ...

The frequency response matrix (FRM) of a multivariable system with \( n_u \) inputs and \( n_y \) outputs can be estimated using arbitrary or periodic excitations. Using only one experiment with random excitations the FRM can nowadays be estimated at full frequency resolution, which is the inverse of the experiment duration [1, 2]. The major disadvantage of stationary random excitations is that no distinction can be made between noise and nonlinear distortions [2]. At the price of a loss in frequency resolution of at least a factor 2, it is possible to separate the noise from the nonlinear distortions via an experiment with non-stationary random signals [3]. Furthermore, for finite samples, the sample input power spectrum is a random process that approximates the desired input power spectrum. Hence, at some frequencies less power is injected than needed to achieve a given signal-to-noise ratio on the FRM estimate.
Via $n_y + 5$ steady state experiments with $n_u$ sets of uncorrelated inputs one can easily separate the noise from the nonlinear distortions in FRM estimates [4, 5]. The major disadvantages of this so-called “robust” method with respect to random excitations are the $(n_y + 5)n_u$ times smaller frequency resolution and the fact that no operational data can be handled.

In this project a “fast” method is developed for estimating the FRM, the noise level, and the level of the nonlinear distortions from 2 consecutive periods of the transient response to one set of uncorrelated periodic inputs that – for all inputs – excites all harmonics in the frequency band of interest. Hence, irrespective of the number of inputs $n_u$ and outputs $n_y$, the loss in frequency resolution (or increase in measurement time) of the “fast” method with respect to stationary random excitations is a factor 2.

**Methodology**

Figure 12 compares the DFT spectrum of 2 consecutive periods of the noiseless steady state response with that of the noisy transient response. It can be seen that the odd DFT frequencies of the noisy transient response contain the sum of the noise and the transient contributions. While the noise part varies randomly over the frequency, the transient part is a smooth function of the frequency. This fundamentally different behavior is used to separate the noise from the transient contribution via a local polynomial approximation of the transient term. Using the local polynomial estimate of the transient term (i) the transient contribution at the excited DFT lines can be suppressed, and (ii) an estimate of the input-output noise covariance matrix is obtained.
In a second step the local polynomial method for random excitations [1, 2] is applied to the transient (leakage) free input-output DFT spectra. The result is an estimate of the FRM and its total covariance matrix (sum of the noise covariance and the nonlinear distortions). Comparing the total covariance with the noise covariance obtained in the first step gives an estimate of the level of the nonlinear distortions.

**Measurement example**

As test case we take an aluminium tooling plate (PE 200) of size 30.4 cm x 61.8 cm x 6.7 mm. The plate is excited under free-free boundary conditions by 2 mini-shakers (B&K 4810) spaced 25.5 cm apart (see Figure 13, left picture). The mini-shakers are connected to the aluminium plate via an impedance head (B&K 8001) and a plexiglass stinger rod of 1.8 cm length (the visible part is 1 cm long) glued into screws of 1 cm length with a bore hole of 4 mm deep (see Figure 13 right picture).

The “fast” method is applied to this $n_u = 2$ input, $n_v = 2$ output system. The random phase multisines have a flat amplitude spectrum with equal rms values for all inputs, and contain 12887 harmonically related frequencies that are uniformly distributed in the band [120 Hz, 600 Hz]. The frequency resolution of the corresponding FRM measurement is 37.3 mHz ($f_s = 2.44$ kHz, $N = 64 \times 1024$ points per period). The first 2 periods of the transient response are measured Figure 14 and Figure 15 (a zoom of Figure 14) show the results: it follows that the nonlinearities are important in the neighborhood of the resonances.

Next the “fast” method is compared with the results obtained with a random excitation (= “arb” method) with the same rms value. Instead of Gaussian noise, we use a random phase multisine excitation with period length $2N$ samples for the “arb” method. The reason for this is that the amplitude spectrum of the multisine is deterministic while that of Gaussian noise is random (Rayleigh distributed). The random phase multisine contains 25772 harmonically related frequencies, which are uniformly distributed in the band [120 Hz, 600 Hz], with flat amplitude spectrum and equal rms value for all inputs.
The frequency resolution of the corresponding FRM measurement is 18.6 mHz ($f_s = 244$ kHz, $N = 128 \times 1024$ points per period). Only one period of the transient response is measured. Figure 15 compares the “arb” with the “fast” estimates. In the frequency bands where the noise is dominant, the mean ratio of the total variance of the “fast” FRM estimate to that of the “arb” estimate is -3.5 dB (see Figure 16), which is in good agreement with the theoretical expected value of -3 dB (the signal energy in the “fast” method is distributed over 2 times less frequencies). In the neighborhood of the resonance peaks the total variance ratio is about 0 dB. This is explained by the fact that the nonlinear distortions are dominant in those frequency bands (see Figure 16), and that for the same rms value of the excitations, the signal-to-distortions ratios of the input-output DFT spectra are exactly the same.

References

2.2.2.5 Nonlinear induced variance of the frequency response function of the best linear approximation to a nonlinear system (J. Schoukens, K. Barbé, L. Vanbeylen, R. Pintelon)

In this project we analyses the variance of the estimated frequency response function (FRF) $\tilde{G}_{BLA}$ of the best linear approximation $G_{BLA}$ to a nonlinear system that is driven by random excitations. $\tilde{G}_{BLA}$ varies not only due to the disturbing measurement and process noise. It will also vary over different realizations of the random excitation because the nonlinear distortions depend on the input realization. It is shown that the variance expression $\sigma^2_{\tilde{G}_{BLA}}$ that is obtained in the linear framework, can also be used to calculate the variance that is induced by the nonlinear distortions.
This validates the common engineering practice where the linear FRF-methodology is often used under nonlinear conditions.

Basic result: Consider a (dynamic) nonlinear, time invariant Wiener system, driven by a Gaussian stationary input $u_0(t)$ with power spectrum $S_{u_0, u_0}$:

$$y_0(t) = g(u_0(t))$$  \hspace{1cm} (1)

Define $G_{\text{BLA}}(q)$ as the best linear approximation of the nonlinear system in mean squares sense:

$$G_{\text{BLA}}(q) = \arg\min_G E \{ |y_0(t) - G(q)u_0(t)|^2 \}$$  \hspace{1cm} (2)

where all expected values $E\{ \}$ are taken with respect to the random input $u_0(t)$. An alternative representation of (1) is to write the output $y_0(t)$ as the sum of its best linear approximation plus an error term:

$$y_0(t) = G_{\text{BLA}}(q)u_0(t) + y_s(t)$$  \hspace{1cm} (3)

where $y_s$ accounts for the difference between the output of the best linear approximation and the actual nonlinear output. For random excitations it is very difficult for an untrained user to distinguish $y_s$ from disturbing noise. The signal $y_s$ is uncorrelated with $u_0$ because it is the residual of the solution of a least squares problem. However $u_0$ and $y_s$ are mutually dependent, there exist a nonlinear relation between both which is a major difference with the classical disturbing noise hypothesis $y(t) = y_0(t) + \nu(t)$ with $\nu(t)$ mutual independent of $u_0(t)$. For that reason the linear noise expressions can not be applied without further analysis to the nonlinear distortions!

During the variance calculations of $\hat{G}_{\text{BLA}}(j\omega)$, fourth order moments like

$$E\{ |X(l)|^2 |U_0(l)|^2 \}$$  \hspace{1cm} (4)

appear, with for example $X(l)$ the DFT-spectrum (discrete Fourier transform spectrum as defined later) of $x(t)$. If $x(t) = \nu(t)$, the expected value (4) can be split because of the mutual independency between $u_0$ and $\nu$, so that

$$E\{ |V(l)|^2 |U_0(l)|^2 \} = E\{ |V(l)|^2 \} E\{ |U_0(l)|^2 \} = S_V(l)S_U(l)$$

The surprising result will be that although $y_s$ and $u_0$ are mutual dependent, it still holds that

$$E\{ |Y_s(l)|^2 |U_0(l)|^2 \} = E\{ |Y_s(l)|^2 \} E\{ |U_0(l)|^2 \} + O(N^{-1})$$  \hspace{1cm} (5)

which leads eventually to the result that the variance on $\hat{G}_{\text{BLA}}(j\omega)$ after averaging over $M$ realizations is given by

$$\lim_{M \to \infty} (M\sigma^2)_{\hat{G}_{\text{BLA}}} (k) = \frac{S_{\nu\nu}(k)}{S_{\nu\nu}(k)} + O(N^{-1})$$  \hspace{1cm} (6)

which is the same expression as in the case of independent disturbing noise $\nu(t)$, with

$$\lim_{M \to \infty} (M\sigma^2)_{\nu_{\text{BLA}}} (k) = \frac{S_{\nu\nu}(k)}{S_{\nu\nu}(k)}$$  \hspace{1cm} (7)
This shows that the expressions of the nonparametric linear framework can also be applied to the more general setting of linear approximations of nonlinear systems driven by Gaussian noise.

### 2.2.2.6  Study of the variance of parametric estimates of the best linear approximation of nonlinear systems

(J. Schoukens and R. Pintelon)

This project analyzes the variance of the estimated parametric best linear approximation $\hat{G}_{BLA}(q, \theta)$ of a nonlinear system that is driven by random excitations. The estimated model $\hat{G}_{BLA}(q, \theta)$ varies not only due to the disturbing measurement and process noise, but also over different realizations of the random excitation because the nonlinear distortions depend on the input realization. For the nonparametric frequency response function estimate it has been shown that the variance expression is still valid in the presence of nonlinear distortions, the same formulas can be used in the linear as in the nonlinear case. This result does not hold for the variance $\sigma^2_{BLA}(q, \theta)$ on the parametric estimate $\hat{G}_{BLA}(q, \theta)$. It is shown in this project that it is still possible to upperbound the variance $\sigma^2_{BLA}(q, \theta)$ using the linear expression, by introducing an additional scaling factor that depends upon the maximal degree of the nonlinearity.

#### Basic results

Linear models are intensively used by engineers to model dynamic systems, even if these are known to be prone to nonlinear distortions. The major reason for that is that the linear theory and the corresponding measurement and modeling procedures are well developed and easy to use. Besides a model estimate, also variance estimates on the estimated model are delivered. For nonparametric frequency response function (FRF) estimates of the best linear approximation (BLA), it is shown in the previous project that the variance expressions for the linear setup are also valid for nonlinear systems. In this project parametric estimates $\hat{G}_{BLA}(q, \theta)$ of the BLA are considered, with $q^{-1}$ the backward shift operator. As such it complements the nonparametric results of. It is shown that the nonparametric result does not carry over to the parametric estimate of the BLA, the linear variance expressions are no longer valid. However, for a nonlinear system with a given maximum degree of nonlinearity, it will still be possible to provide an upper bound starting from the linear variance expression.

The main message of this paper for the practicing engineer is that it is always necessary to make a nonlinearity analysis each time that a parametric linear model (approximation) is identified. Without such an analysis the user has no idea how to generate safe and not too small variance bounds.

Nevertheless it is still possible to use the linear variance bounds if a proper correction factor is applied. The problem is that this correction depends upon the degree of the nonlinearity, and in practice contributions of different degrees are added on top of each other. However, assuming that the dominating nonlinear distortions are of 2nd and 3rd degree (which is in many applications a
realistic assumption), a correction factor of 7 can be applied. If the user wants to generate less conservative uncertainty bounds, it is necessary to make a nonlinear distortion analysis in order to detect whether or not nonlinear distortions are dominating over the disturbing noise.

The major reason for the striking difference in behavior between the parametric and the nonparametric FRF estimate (where no correction factor is needed) is that the FRF is calculated frequency per frequency, while in a parametric estimate, the information at all frequencies is recombined in a few parameters.

### 2.2.2.7 Frequency Response Function measurements using concatenated data records (J. Schoukens, G. Vandersteen, R. Pintelon)

In this project we developed a nonparametric method to measure the frequency response function (FRF) of a linear dynamic system that allows a series of sub-records to be concatenated in one long data record without suffering from the leakage and transient errors. The method combines data blocks (of different length) into a single record, resulting in an increased frequency resolution. The analysis is based on the recent insight that leakage errors in the frequency domain have a smooth nature that is completely similar to that of initial transients in the time domain. The method is applicable to both single-input-single output (SISO) and multiple-input-multiple-output (MIMO) systems. The results are illustrated on simulations and experimental data.

**Introduction and results of the project**

Measuring the FRF of a linear dynamic system, together with the variance of the disturbing process and measurement noise is an old problem that is considered to be well solved and completely understood. The major disadvantage of the nonparametric approach is the presence of leakage that is intrinsically linked to the time-frequency domain transform. Even in the absence of disturbing noise, the FRF-measurements can be corrupted by these errors due to windowing effects: only a finite length record can be measured and processed. One possibility to get around these problems is to measure an integer number of periods of the steady state response of the system to a periodic excitation. This requires that the system’s transient response decayed well below the noise level, which is done at the cost of lost measurement time since the transient information cannot be used. Moreover, in many applications the user wants to stick to random excitations, sometimes for technical reasons, sometimes by tradition in a given application field.

Until the 80’s, leakage errors on FRF-measurements were studied at the input and output signal level, without considering the linear system relation between the input and output. In a series of papers the importance of this relation was recognized: In FRF-measurements, the errors are due to unknown past inputs and missing future outputs. Both effects are highly structured, with smooth frequency characteristics. It is this key observation that led to a new analysis of the existing methods, and to a new better performing method to estimate the FRF and the power spectrum of the disturbing noise, called ‘the local polynomial method’ (LPM). The basic idea in this method is to
make a local polynomial interpolation over neighboring frequency lines to estimate the FRF at the central frequency, and to eliminate, at the same time, the leakage and transient effects. The LPM outperforms the classical methods, the leakage errors are reduced to much lower levels at a cost of increasing the computation time with a factor 1000 compared with windowing methods. This is not an issue with the actual available computing power as the solution can still be obtained in a few seconds for records with a length of a few thousands points, while the leakage error is reduced with several orders of magnitude, depending upon the system and the record length.

In this project we extended this method to process also concatenated data records that can be of unequal length. If for some reason, a number of shorter sub-records is available, then it turns out that it is advantageous to process them all at once, considering the data to come from one single experiment. This results in a higher frequency resolution of the FRF estimate so that resonances with lower damping can be measured better. Simultaneously, the leakage induced variance is reduced with about 6 dB and the leakage induced bias with about 20 dB. The sensitivity to disturbing noise grows proportionally to the number of sub-records. However, when accounting for the increased number of measurement points that is available due to the increased frequency resolution, it turns out that the noise sensitivity is not affected.

### 2.2.2.8 Identifying a Wiener system using a variant of the Wiener G-Functionals (Koen Tiels, Johan Schoukens)

In this work a variant of the Wiener G-Functionals [1] is proposed to identify for example block structured systems (Wiener, Hammerstein and Wiener-Hammerstein). In this work the method is illustrated on the noiseless case for the Wiener system given in Figure 17.

\[
G_1 \begin{pmatrix} x \\ f(x) \end{pmatrix} = x + \alpha_2 x^2 + \alpha_3 x^3
\]

*Figure 17: Wiener system with a static nonlinearity*

with \( G_1 \) a second order Chebychev filter and \( f(x) \) a static nonlinearity.

The method consists of the following steps:

1. Determine the best linear approximation (BLA) of the system and estimate a parametric model of the BLA;
2. Construct orthonormal basis functions with the poles of the BLA obtained in step 1;
3. Estimate the static nonlinearity;
4. Validate the model.

**Step 1: best linear approximation**

Using a random phase multisine as input signal \( u \), we know that the BLA of the system equals

\[
G_{BLA} = G_1 G_{BLA,f} = G_1 e
\]
with $c$ an unknown constant. We see that the BLA of the system has the same poles as $G_1$. When a parametric model is fitted on the BLA, a good estimation of the poles of $G_1$ is obtained. Consider for example a complex pole pair $\xi$ and $\xi^*$.

**Step 2: orthonormal basis functions**

We use Takenaka-Malmquist orthonormal basis functions that can deal with real and complex poles [2]

$$F_k(z) = \frac{\sqrt{1 - |\xi_k|^2}}{z - \xi_k} \prod_{i=1}^{k-1} \frac{1 - \xi_i^* z}{z - \xi_i}, \quad k = 1, 2, \ldots, n, \quad \xi_i \in \mathbb{C}, \quad |\xi_i| < 1$$

(2)

By combining two complex conjugated poles real impulse responses are obtained [2]. One extra basis function is chosen to account for the direct term that is visible when the partial fraction expansion of $G_{BLA}$ is made. For example for a second order system:

$$G_{BLA} = \frac{r}{z - \xi} + \frac{r^*}{z - \xi^*} + k$$

(3)

$$F_{n+1}(z) = k$$

(4)

Let $x_i$ be the input signal $u$ filtered with the $i^{th}$ basis function. Then the intermediate signal $x$ can be approximated by a linear combination of the signals $x_i$.

**Step 3: estimate the nonlinearities**

The signals $x_i$ are applied to the input of a MISO static nonlinear system with the signal $y$ as output. Identifying this system is a problem that is linear in the parameters and it is solved using a least squares estimator.

**Step 4: validation**

To validate the obtained model, a random phase multisine $u_{real}$ is applied to the input of the system given in Figure 17. By increasing the number of orthonormal basis functions, the mean square error on the modeled output can be made arbitrarily small. The better the initial pole estimates, the smaller the number of basis functions that is needed.

**References**


2.2.2.9 Bounded operation of unstable nonlinear models under small random burst excitations
(Laurent Vanbeylen, Anne Van Mulders and Johan Schoukens)

1 Motivation and goal

A large class of nonlinear plants can be very well approximated via the family of polynomial state-space models (with a polynomial state evolution in the state and input). It has good black-box approximation capabilities, and the model can be obtained from input-output measurements via a least-squares data-fitting approach (Paduart et al., 2010). The problem is that no stability guarantees are given for the obtained nonlinear model; only the underlying linear dynamics are easy to analyse. It is therefore desirable to investigate (automatically) how a given state-space model \( x(t+1) = f(x(t), u(t)) \) behaves under a given random input when no stability information is given. Moreover, an unstable system's state can stay within a given bounded region for very long periods of time and with a high probability. In this work, we propose a method that allows one to estimate the probability density function (pdf) of a future state, given the (smooth) state space equation, the initial state and the nature of the random input, consisting of a Gaussian term with known power spectrum and a known deterministic term. Other possible applications include the analysis of the start-up behaviour of nonlinear oscillators, the investigation of physical (white-box) models, and controlled nonlinear plants with random noise on top of the deterministic reference signal.

2 The importance of the region of attraction

Assuming that the unforced system considered has an isolated, asymptotically, locally stable equilibrium at the origin, means that, for a zero input, the state tends towards the origin from any initial state in a given domain around it. The largest domain with this property is called the region of attraction (ROA). Any state starting outside, tends to drift away either towards other equilibria, to limit cycles, to chaotic attractors or to infinity. This is a purely nonlinear effect due to the nonlinear terms in the state-evolution equation. When the random input becomes active, starting from a state inside the ROA, at each time step there is a random "jump" inducing a risk of crossing the ROA's boundaries. The larger the input variance, the larger the probability of being kicked out of the ROA over a given time horizon. In the method, it will be assumed that the input is a burst excitation, so that it is only nonzero on the time span \([0, \tau]\). Therefore, the pdf of the state \(x(\tau)\), integrated out over the ROA, yields the probability of getting a response tending to zero (which guarantees a bounded operation).
**3 Suggested approach**

The pdf $p_{x(\tau)}(x(\tau))$ of the future state $x(\tau)$ can be calculated as the integrated form of a higher-dimensional joint pdf based on all states and inputs:

$$p_{x(\tau)}(x(\tau)) = \int_{-\infty}^{+\infty} p_{x(\tau)|u}(x, x(\tau)|u) dx du$$

With $x^T = [x(1) ... x(\tau - 1)^T]$ and $u^T = [u(0) ... u(\tau - 1)]$; the integrand can be rewritten as $p_u(u)p_{x,x(\tau)|u}(x, x(\tau)|u)$ with $p_u$ a known Gaussian pdf, and $p_{x,x(\tau)|u}$ a known Dirac delta distribution imposing the state evolution equation at $t = 0 ... \tau - 1$. If the input variance is small, the integral can be well approximated at any point of the state space via the Laplace integration method. This, in turn, requires the solution of a constrained optimisation problem, which can be interpreted as the most likely input-state combination driving the state from its initial position to the pdf's argument.

The results of the pdf estimation applied on a 2-dimensional example, in which the ROA is known to be the unit disk, are shown in Figure 18.

**Figure 18** Contour lines of the estimated $\log p_{x(\tau)}(x(\tau))$; it is seen that random Monte Carlo trajectories stay in the high pdf region, as expected.

**Reference:**

Flutter is an aerelastic phenomenon that makes structures oscillate when surrounded by a moving fluidum. Flutter can lead to fatigue and/or failure on the wings, flaps and fuselage of an airplane. Laborious testing needs to be done on aircraft to ensure safe operation within a certain flight envelope. While flutter is inherently nonlinear, most models use a linear framework to predict the critical speed at which oscillations might occur. The aim of this work is the construction of a nonlinear model to more accurately predict the onset of oscillatory behavior, on the basis of wind tunnel test measurements.

**Experimental setup**

In a first step, we built an experimental setup with which we can create flutter under controlled conditions. This first setup, shown in Figure 19, is a cantilevered airfoil. The sections we use for this experiment are hotwire-cut out of polystyrene. A computer controlled hotwire machine has been made to aid with the cutting of airfoils. To keep the sections from producing lift at zero angle of attack, we solely use symmetrical NACA airfoils. Because the velocity of the wind tunnel we have at our disposal is limited to 50 m/s and because of safety reasons, we want the wing to get unstable at as low a wind speed as possible. Therefore, a system has been devised that allows the modal properties of the wing to be altered. It consists of a rail on which small weights can be fixed. By tuning the distance from the weights to the aerodynamic centre of the airfoil, the frequency of the first torsional mode can be brought closer to the frequency of the first bending mode. When wind is applied, these modes get even closer to one another and because flutter occurs when these modes start to couple, a lower flutter speed is achieved through the use of this tunable system. To measure and tune the modal parameters of the setup, a shaker and laser vibrometer are used. When actually under test, the shaker cannot be used because once the airfoil gets unstable, the vibration would damage the shaker.

As a second step, we are currently building a setup that also allows the use of forced excitations. The setup is shown in Figure 20. Conceptually it is closely tied to a standard two degrees of freedom (DOF) configuration that is often used for flutter research. The advantage of the proposed setup is that instead of using linear springs to characterize the airfoil's pitch and plunge stiffness, it uses...
linear motors. Not only does this allow us to choose the stiffness of the pitch and plunge motion, but the linear motors enable us to impose an arbitrarily chosen excitation signal upon the airfoil. In doing so, we hope to better understand the flutter phenomenon and characterize its nonlinear behavior [1].

**Conclusions**

We are able to create flutter in a reproducible manner with the cantilevered setup. We also have control over the speed at which it occurs. At the moment of writing the actively controlled setup has not been finalized.

**Reference**


2.2.2.11 Unraveling polynomial nonlinear state-space models into Wiener-Hammerstein blocks (Anne Van Mulders, Laurent Vanbeylen, Johan Schoukens)

**System and model candidates**

Suppose that one wants to identify a model of a Wiener-Hammerstein system (Figure 21). A Wiener-Hammerstein system consists of two linear dynamic subsystems that are separated by a static nonlinearity.

![Figure 21 Wiener-Hammerstein system.](image)

Several models can be considered as an option: block structured models, but also black box models. A drawback of the block structured models is the difficulty to determine initial estimates. Especially the model orders of the two linear blocks are unknown beforehand.

When using black box models, the nonlinearity will pop up in a natural way at a suitable place during the optimisation and the user does not have to bother about the model orders of the linear blocks.

*Our goal is to transform a black box model into a block structured model.* This last model is easier to interpret than the first one, which contains no easily accessible information about the structure of the system.
**Black box model class**

The considered model is a Polynomial Nonlinear State-Space (PNLSS) model [1, 2]. It can describe the behaviour of a vast amount of nonlinear systems, amongst which several block structured systems. The drawback is that it contains a high number of parameters. In order to gain physical insight and to reduce the number of parameters significantly, it is interesting to dig deeper and to try to find the Wiener-Hammerstein structure behind this complex model.

The PNLSS model can be written as a state-space expression in discrete time:

$$
\begin{align*}
    x(t + 1) &= f(x(t), u(t)) \\
    y(t) &= h(x(t), u(t))
\end{align*}
$$

$x$, $u$ and $y$ are the states, the input(s) and output(s). $f$ and $h$ are polynomial functions.

Although the description of a Wiener-Hammerstein system can often be done with few parameters, a full parameterisation of a PNLSS model soon results in a very large number of parameters, growing combinatorially (e.g. order $n = 6$ and powers 1, 2 and 3 in the polynomials results in 833 parameters).

**State transformations affecting model sparsity**

As any state-space model, the PNLSS model can be represented in an infinite amount of ways by means of state transformations, without affecting the input-output behaviour. In contrast to linear models, in which only linear similarity transforms can keep the model type unchanged, in the nonlinear case, both linear and nonlinear transformations can create a new model that fits within the same model class (i.e. preserving the same symbolic representation). We have observed that, using a full parameterisation [1] of the PNLSS model, the existing identification method destroys the sparse structure of the model equations, creating a huge number of redundant nonzero parameters.

**Achieving the goal**

The goal of this research, which is to transform an initial, general model into a structured one, is obtained in several steps. First, an optimisation method transforms the PNLSS model nonlinearly, such that only one of the states contains nonlinear terms. Secondly, the states are transformed linearly, such that the number of nonlinear terms in this state equation is reduced to a minimum. Then, a final linear transformation is found via numerical optimisation to retrieve a structure in the parameter matrices that allows the model to be split in parts directly. Those parts are the two state-space descriptions of the linear blocks and the coefficients of the nonlinear terms of the nonlinear block. The method has been successfully tested on simulation examples, where the nonlinearity of the Wiener-Hammerstein model is polynomial. The next step is to adapt the
routines so that they are also applicable on more general data (i.e. not generated by a Wiener-Hammerstein system with polynomial nonlinearities).

References

2.2.2.12 Identification of a wet clutch system (Dhammika Widanage)

A wet clutch is a mechanical device that transmits torque from an input axis to an output axis via fluid friction. An electro-hydraulic pressure-regulated proportional valve regulates the pressure inside the clutch which brings about the engagement of the piston with the friction plates. A model describing the relation between the current applied to the valve and the resulting pressure during the filling stage of the clutch is required to bring about a smooth engagement using either iterative learning control or model predictive control. The device on which the measurements are performed is shown in Figure 22.

With several sets of current and pressure signals measured a nonlinear polynomial state space model is derived and is validated. A comparison between new measured pressure signal and the nonlinear model output is shown in Figure 23 (Top). It is seen that the nonlinear model yields better results than a linear model when validated with the same data Figure 23 (bottom).

**Figure 22 Wet clutch test bench**

**Figure 23 Measured and model fit. For both figures, Solid line: Measured pressure. Dotted line: Model output. Thick line: Error. Top figure: Nonlinear model output. Bottom figure: Linear model output.**
2.3 TEAM C: APPLIED SIGNAL PROCESSING FOR ENGINEERING (ASPE)

2.3.1 Introduction to Applied Signal Processing for Engineering (ASPE)

The current trend in the microwave world is to build systems with extremely high performance demands to meet the challenges of modern telecommunication applications. As a result, both the linear and the nonlinear operation of these devices has to be modelled with accurately, but with models that are numerically cheap to evaluate. The linear models that are still used for the mainstream developments of circuitry, are very good at describing the small signal behaviour components, subsystems and systems. However, there is an ever increasing demand for nonlinear models that are easy enough to use and to understand, but nevertheless are capable to describe power efficiency or harmonic distortion under realistic operating conditions. The main goal and the common denominator of the work performed in this team is ‘to measure, understand and model devices and systems that operate at RF and microwave frequencies’

To reach this goal a two-layered approach is proposed:

- **Gain insight in the device behaviour.** This step can be put in parallel with the frequency response extraction or the S-parameter measurement if only the class of linear systems is considered. To be able to extend this towards nonlinear systems, a restriction of the class of allowable nonlinear systems is needed. The Periodic In Same Period Out (PISPO) system class is wide enough to contain (saturating) nonlinear amplifiers, mixers, and even voltage controlled oscillators. A system belongs to the PISPO class if a periodic excitation waveform results in a periodic output with the same periodicity. Appropriate data preprocessing and the adequately obtained measurement data allows a trained user to understand the mechanisms that govern the general behaviour of the Device Under Test (DUT). From an identification point of view, this approach is essentially a non-parametric modelling step.

- **Extract a parametric model for the device.** This can be put in parallel with the extraction of a rational transfer function model for the DUT in the linear case. To be of practical use, this model has to integrate seamlessly in existing simulation frameworks. Special caution is to be used here to avoid that the model ‘user lives up to non realistic expectations. It happens all to often that models are ‘sold’ as soap, leaving it up to the user to detect whether or not the response of a pile of numbers can be trusted. Fortunately, this can be circumvented by a trustworthy validation step. To this end, the model output is compared with the measurements as obtained during the estimation of the first layer model. Differences between model and measurement can then be used to decide whether or not the proposed model structure meets the user demands based on a fair, quantified comparison norm.

The contributions of the team all contribute in some way to the realisation of this long-term goal. The different contributions are first put in perspective below, and next are described in some more detail.

- **Instrumentation setup contributions.** The complete characterisation of a nonlinear system is much too ambitious goal to realize in a single step. Often, it will even be questionable whether it makes sense to chase this goal at all. Most applications of nonlinear devices use the device for a limited range of possible operating conditions, and if the model is capable to predict the device behaviour under these contraints, the demands of the user are fulfilled. The most common boundary conditions involve the selection of the signal class, the impedances that are provided at the ports and the biasing levels. To measure nonlinear devices or components, it is of vital importance that the setup is able to mimic real operation conditions during as closely as possible. Thereto, highly flexible instrumentation setups are required. A flexible non-linear network analyser was developed to this end. The
device combines the advantages of reconfigurability and ease of use and provides an efficient and easy to use data handling capability.

- Instrumentation calibration contributions. As for today, the instrument fully handles the waveform calibration for two- and three-port measurements in CW regimes. Additional contributions in the phase calibration allow to calibrate and verify waveform measurements for the modulated and pulsed operation.

- Modelling contributions. In the framework of linear time invariant systems, a black box errors-in-variables approach is proposed that does not rely on circuit descriptions. In the end, the proposed black-box approach delivers models that properly describe the linear dynamics of the DUT, detect the presence of modelling errors and have by far better numerical properties than their circuit-based equivalents. On top of that, the model extraction operates almost automatically. In the non-linear non-parametric range of models a ‘energy-transport’ model is proposed that yields simple, yet effective, ways to estimate the dominant non-linear energy transport mechanisms that are present in the behaviour of the nonlinearity. Using this approach allows to increase the users’ level of confidence in the model and mostly avoids the otherwise tedious problem of model structure selection. Parametric models that cover a wide range of frequency and power were then identified based on this previously obtained knowledge of the dominant influences in the model.

2.3.2 Activities in a nutshell

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2.3.3 Short Description of the Research Projects of Team C

2.3.3.1 Multirate Cascaded ΔΣ Converters for Wireless Applications (Lynn Bos)

Multirate cascading, which means that a different sampling frequency (Fs) for each stage in a ΔΣ modulator is used, has been exploited to extend the signal bandwidth of discrete-time bandpass ΔΣ modulators with respect to the state-of-the-art performance. Thanks to this increased bandwidth, the direct digitization of the 20 MHz wide FM band centered at 88-108 MHz is targeted. A feasibility study of a multirate cascaded detuned bandpass discrete-time ΔΣ modulator, with the conceptual scheme of the architecture in Figure 24, has been performed.

![Figure 24: Conceptual scheme of multirate cascaded detuned bandpass discrete-time ΔΣ modulator](image)

The first stage uses a fourth order traditional $F_s/4$ structure centered at 100 MHz and thus a sampling frequency of 400 MHz. The second order second and third stage operate at twice the sampling frequency (800 MHz) and are centered respectively to the left or the right of the first stage by using an $F_s/8.7$ and an $F_s/7.47$ structure. This architecture choice gives rise to the composite noise transfer function shown at the right of Figure 24 in which the signal bandwidth is extended to 20 MHz.

The lower sensitivity to the quality factor and the center frequency of each resonator in this wideband ΔΣ converter is exploited to relax the resonator requirements, which in turn relaxes
amplifier specifications and reduces the power consumption. However, the high sensitivity of the architecture to analog mismatches requires a calibration of the digital cancellation filters.

Behavioral simulations of the resonators led to the extraction of the amplifier requirements and their sensitivity to process variations. In spite of the aforementioned optimizations, the aggressive bandwidth and center frequency targets, set stringent specifications on the amplifiers and switches due to the high sampling frequency in combination with large capacitive load.

From this study, we conclude that this architecture can reach sufficient performance for the direct digitization of the FM band if a calibration method is used and after careful design of the amplifiers and switches. Taking into account the estimated power consumption, a state of the art figure of merit can be achieved.

### 2.3.3.2 Analysis of the biological composition of fresh water lakes by measuring and modeling

(Diane De Coster, Gerd Vandersteen, Yves Rolain)

**Introduction**

To avoid blooming of algae, online monitoring of the density is necessary because the system is dynamic and even chaotic. Biomass growth monitoring is a very useful tool to predict blooming in fresh water lakes. This work is a step towards an online monitoring setup for this growth. We want to create a model that is able to identify fluorescence peaks of algae to distinguish different groups of algae.

**Characterization of algae growth**

Algae blooms have a seasonally recurring behavior, which is dynamic and even chaotic or irregular in amplitude. It is difficult to model this, even with the use of seasonal forcing in the model [1]. Prediction of the concentration of algae is very highly conditioned on accurate measurements of the density of these organisms. Fluorescence spectrometry is expected to enable those measurements. The 'Ramses' radiometer is used for the hyperspectral analysis of the water surface. We try to differentiate between three groups of algae.

Algae in fresh water lakes are not inherently fluorescent so chemical labeling is necessary. By illuminating the labeled algae with modulated visible light different types of algae will emit
fluorescence light at different wavelengths. The problem is that the responses are overlapping. Due to this the results of the algae concentration are not very accurate and the number of groups that we can distinguish is limited. To solve this we can model the fluorescence spectrum as a white spectrum that is filtered by a linear time invariant system in the s-domain [2]. With the partial fraction expansion representation of the transfer function the relative concentration of the algae can be yielded by the surface beneath each peak. A preliminary model is shown in Figure 25, where the frequencies range from 320 to 930 THz. Visually the highest peaks are located around 370, 420 and 530 THz. This characterizes the three groups of algae.

**Detection of the algae**

Another way to improve the resolution of the concentration results of the algae is to add measurements in another frequency range. Therefore we want to evolve to a combined measurement with mini-spectrometers and sub-mm wave detectors to measure the algae’s specific factors. By doing this we hope to extract more and better information about the biological composition of the lakes by studying the behaviour of the algae in the THz range and visible light range. Due to the small intensities of the measured signals a miniaturized lock-in detection will be needed and developed. By using this technique the interfering light is removed to have a proper detection of the algae response alone.

**Conclusion**

To characterize the biological composition of the fresh water lakes we want to use multisensor data to enable an efficient determination of the algae concentration. A model of the fluorescence spectrum can be realized with a linear time invariant system. A first attempt of fluorescence model seems to work.

**References**


**2.3.3.3 Use and modeling of overtone resonances in FBAR resonators operating at RF frequencies (Mohamed El-Barkouky)**

Nowadays telecommunication systems have an increasing demand for high quality factor, small size and low power consumption components. Thin film bulk acoustic wave resonators (FBAR) technology replaced both the bulky off-chip surface acoustic wave (SAW) components and the low quality factor on-chip tank circuits in many commercial applications such as filters and duplexers.
This work extends the use of FBAR components to higher frequencies when the overtone resonances of the device are considered. First, a broadband measurement of the FBAR resonator shows that several high quality resonance modes are present at odd overtones. Existing modeling techniques are then extended towards their use in design at these overtone modes. To increase the quality of the models and validate the models against the real device behavior, a system identification based approach is proposed. It is shown that this new model empowers the design at overtone modes and increases the physical insight in the parasitic behavior of the devices. A number of integrated CMOS and discrete demonstrators are designed based on this modeling approach to show both the feasibility of the overtone designs and their performance. Several configurations are investigated in detail through extensive simulations, and one design is realized and measured in detail.

2.3.3.4 Advanced calibration and Instrumentation setups for nonlinear RF devices (Liesbeth Gommé)

Modern wireless telecommunication applications are omnipresent in our day-to-day lives. One can no longer imagine life without the highly power-efficient and low-cost technology fortifying the advances in wireless telecommunication. In order to satisfy the performance requirements, components are driven beyond their linear region of operation. Understanding the behaviour of nonlinearities is therefore essential when designing components that take part in a telecommunication loop. One of the first setups capable of capturing the nonlinear behaviour of an RF component was the Large-Signal Network Analyser (LSNA). When performing measurements with the LSNA, systematic errors arise due to imperfections of the measurement instrument. In order to minimise these errors a calibration is necessary. Calibration boils down to comparing the known characteristics of a presumed ideal reference element or calibration standard to its measured response. The differences are attributed to the non-ideal response of the measurement instrument and should be eliminated. This dissertation deals with the calibration of measurement instrumentation used for the characterisation of the nonlinear behaviour of RF devices. Unfortunately, one of the key components in the calibration procedure of such instrumentation is restricted to a coarse frequency grid. In this work a reference device and a reference signal are studied as two standards allowing a dense frequency grid calibration. A reference device that is passive, inheriting a high stability and repeatability is proposed as a calibration standard. A reference signal is specifically designed to meet the requirements of a dense frequency grid calibration. The performance of both techniques is discussed in full detailed and paves the way towards a calibration on a dense frequency grid.
2.3.3.5 Design, realization and measurement of Phase Locked Loops (PLLs) using advanced signal processing techniques. (Maulik Jain; Gerd Vandersteen)

The aim of this research is to apply the state-of-the-art signal processing techniques to design, realize and measurement Phase Locked Loops (PLLs) (Figure below). The operation of such devices can be approximated using linear system blocks in the phase domain.

The aim is to port the results of the nonlinear distortion analysis using the Best Linear Approximation paradigm to PLL applications. One of the issues is that the frequency divider only changes its value to discrete levels. Hence, a continuous-valued multisine excitation for the frequency division cannot be applied straight away. The first target is to identify and quantify the sources of nonlinear distortion in the PLL based on the Best Linear Approximation.

For demonstration purposes, a full custom 1GHz PLL CMOS chip was designed which handles frequency division ratios from 8..1023. A PIC microcontroller will set the frequency division ratio as a multisine and the output will be measured and analyzed using microwave instrumentation. There is also the possibility to directly provide the control voltage to the VCO to evaluate the nonlinear performance of only the VCO.

Figure 26 Components of a Phase Locked Loop
2.3.3.6 3D Nonlinear Least Squares Position Estimation in a Monolithic Scintillator Block
(Zhi Li, Gerd Vandersteen)

Last year, it has been investigated [1] to build a model and use nonlinear least-squares estimation method to find the 3D 511 keV gamma ray interaction position simultaneously in a monolithic scintillator based detector in Positron Emission Tomography (PET) systems. The purpose of this work is to obtain the position without having to acquire training data sets or to calibrate the model parameters. This was achieved using a model based on virtual mirror sources and solid angle estimation of the light profiles measured by an Avalanche Photo Diode (APD) array reading out the monolithic block. The detector used in this study (figure) consists of a 20x20x10 mm3 Lutetium Oxyorthosilicate (Lu2SiO5 or LSO) scintillator block coupled to two Hamamatsu S8550 APD. The APD arrays consists of 8x4 pixels, each measuring 1.6x1.6 mm2. Every APD pixel is equipped with its individual readout chain consisting of a CREMAT CR-110 front-end preamplifier, a CAEN N568B spectroscopic amplifier channel (16 channels/module), and a CAEN V785 peak sensing ADC channel (32 channels/module).

Good result has been achieved in both simulation and experiment data. Applying the approximate solid model with 4 virtual sources to experimental data we measured an average resolution over the complete block of 1.85 mm FWHM in the X direction and 2.5 mm FWHM in the Y directions and 3.4 mm FWHM in depth of interaction (DOI). If the influence of the 1.2 mm FWHM beam size is subtracted from these results, the intrinsic resolution in X and Y direction becomes 1.4 mm and 2.2 mm FWHM respectively. An evenly distributed APD geometry and more accurate mounting of the LSO block on the APD matrices will probably improve the resolution in Y direction. The estimated intrinsic DOI resolution is estimated at 2.6 mm FWHM.

Those resolutions are comparable to the existing method like Maximum Likelihood [2] and Neural Network [3], and the method has the advantage that no pre-calibration are needed, which is time consuming. The third dimension (DOI) information is achievable in this method make it more attractive since current commercial PET system can not supply this information although it is important to provide more uniform image resolution.
References:

2.3.3.7 Modeling of thermal dynamics in Laplace and Warburg Variable
(Griet Monteyne, Gerd Vandersteen)

Introduction
This work is related to geothermal heat pumps. To check the thermal balance of the ground, heat diffusion phenomena need to be modeled. In the present study different model extraction techniques for such heat diffusion problems are discussed, namely using rational transfer function models in both the Laplace and the Warburg domain. The experimental verification is based on temperature measurements of the heat diffusion in an isolated bar. The best rational transfer function models in the Laplace variable $s$ and in the Warburg variable $\xi$ are compared, demonstrating that the Warburg domain has better extrapolation capabilities when it comes to extrapolating towards lower frequencies.

Measurement and Analysis
The experimental setup consists of an iron bar wrapped in rock wool (see Figure 27). The temperature is varied by use of a power resistor located at the left side of the bar that is switched on and off using a periodic pseudorandom binary sequence alike signal.

The temperature is measured at two different axial positions ($T(0,s)$ and $T(x,s)$ in Figure 27) by use of digital temperature sensors. Eight periods (total duration of 11h18min) are measured both for the estimation and the validation data.

The data is then analyzed using the MATLAB Fdident Toolbox [1] [2], taking the transient effects into account [3]. Only these non parametric Frequency Response Function (FRF) estimates that are characterized by a variance that is smaller than the estimated FRF value are used in the identification step. This selection results in a set of 80 frequency lines below 0.015Hz. The 60
highest frequency lines (above 0.004Hz) are selected from the original 80 frequency lines to check the extrapolation capabilities of the model (see Figure 28).

Both parametric models in $s$ and $\sqrt{s}$ are well suited to model the heat diffusion in an isolated bar. The rational model in the Warburg domain has better extrapolation capabilities when it comes to extrapolating towards lower frequencies compared to the model in the Laplace domain.

References

2.3.3.8 Measurement, Modelling and Identification of Microwave Systems (Yves Rolain)

The current trend in the microwave world is to build systems with extremely high performance demands to meet the challenges of modern telecommunication applications. As a result, both the linear and the nonlinear operation of these devices have to be modelled accurately, with models that are numerically cheap to evaluate.

The linear models that are still used for the mainstream developments of circuitry, are very good at describing the small signal behaviour components, subsystems and systems. However, there is an ever increasing demand for nonlinear models that are easy enough to use and to understand, but nevertheless are capable to describe power efficiency or harmonic distortion under realistic
operating conditions. The main goal and the common denominator of the work is 'to measure, understand and model devices and systems that operate at RF and microwave frequencies'.

To reach this goal a two-layered approach is proposed:

- **Gain insight in the device behaviour.**
  This step can be put in parallel with the frequency response extraction or the S-parameter measurement if only the class of linear systems is considered, and is based on the BLA extraction under multitone excitation. To be able to use this framework for nonlinear systems, a restriction of the class of allowable nonlinear systems is needed. The Periodic In Same Period Out (PISPO) system class is wide enough to contain (saturating) nonlinear amplifiers, mixers, and even voltage controlled oscillators. A system belongs to the PISPO class if a periodic excitation waveform results in a periodic output with the same periodicity.
  Appropriate data pre-processing and measurement allows a trained user to understand the mechanisms that govern the general behaviour of the Device Under Test (DUT). From an identification point of view, this approach is essentially a non-parametric modelling step.

- **Extract a parametric model for the device.**
  This can be put in parallel with the extraction of a rational transfer function model for the DUT in the linear case. To be of practical use, this model has to integrate seamlessly in existing simulation frameworks. Special caution is to be used here to avoid that the model user lives up to unrealistic expectations. It happens all too often that models are ‘sold’ as soap, leaving it up to the user to detect whether or not the response of a pile of numbers can be trusted.
  Fortunately, this can be circumvented by a trustworthy validation step. To this end, the model output is compared with the measurements as obtained during the estimation of the first layer model. Differences between model and measurement can then be used to decide whether or not the proposed model structure meets the user demands based on a fair, quantified comparison norm.

The different contributions are first put in perspective below

- **Instrumentation setup contributions.**
  The complete characterisation of a nonlinear system is much too ambitious goal to realize in a single step. Often, it will even be questionable whether it makes sense to chase this goal at all. Most applications of nonlinear devices use the device for a limited range of possible operating conditions, and if the model is capable to predict the device behaviour under these constraints, the demands of the user are fulfilled.
  The most common boundary conditions involve the selection of the signal class, the impedances that are provided at the ports and the operating point selection. To measure nonlinear devices or components, it is of vital importance that the setup is able to mimic real operation conditions. Thereto, highly flexible instrumentation setups are required.

- **Instrumentation calibration contributions.**
  As for today, the instrument fully handles the waveform calibration for two- and three-port measurements in CW regimes. Additional contributions in the phase calibration allow calibrating and verifying waveform measurements for the modulated and pulsed operation.

- **Modelling contributions.**
  In the framework of linear time invariant systems, a black box errors-in-variables approach is proposed that does not rely on circuit descriptions. In the end, the proposed black-box approach delivers models that properly describe the linear dynamics of the DUT, detect the presence of modelling errors and have by far better numerical properties than their circuit-based equivalents. On top of that, the model extraction operates almost automatically. In the non-linear non-parametric range of models a block oriented multi-port approach is preferred as it remains close to the physical structure of the system.
2.3.3.9 MIMO Parallel Hammerstein Identification
(Maarten Schoukens and Yves Rolain)

Introduction

An identification method for multiple input multiple output (MIMO) parallel Hammerstein systems, (see Figure 29) is proposed. It is a generalization of the method proposed in [1], for the case of single input single output.

The MIMO parallel model captures coupled nonlinearities, and power-dependent dynamics (e.g. moving resonance).

The restriction is that the structure only allows nonlinear systems with a dominant input nonlinearity (e.g. RF power amplifiers).

The literature contains identification methods for single branch MIMO systems [2], [3] or parallel Hammerstein (sometimes called Uryson) systems [4], [1]. But there is not much work performed around MIMO parallel Hammerstein systems.

Model and method

The model class: The model structure is a block-structured MIMO parallel Hammerstein model as shown in Figure 30. The static nonlinear blocks are modeled using polynomial functions of the input u(t). The LTI blocks can be represented using a nonparametric frequency response function, or a parametric rational function in s or z-1.

Noise framework: Only output noise is considered.

The identification framework: A black box approach starting from input-output measurements of the system. It can handle a variable number of inputs and outputs. The order of the static nonlinearity can be set by the user, as well as the number of parallel cascades of the different Hammerstein branches.
First, the overall dynamics are estimated in least squares (LS) sense. Second, these dynamics are decomposed, giving an estimation of the LTI blocks. Finally, the static nonlinearities are estimated using a LS estimator.

**Results:** The identification method is tested on a simulation example, giving promising results shown in Figure 30. The errors of the MIMO parallel Hammerstein model are 20 to 30 dB lower compared to the errors made by a linear model of the simulated system. The simulation proves that the method performs well both for highly nonlinear and moderate nonlinear systems.

**References**


**2.3.3.10 Identification of distillation columns using multisine excitation**

(*Diana Ugrayumova, Gerd Vandersteen, Rik Pintelon, Bart Huyck*, Jullian Bonilla*, Filip Logist* and Jan van Impe*)

(*KULeuven*)

**Introduction**

Distillation is nowadays a widely used separation technique. A high purity separation is achieved by increasing the number of trays (or the column height) or by increasing the energy consumption. To make the distillation process more efficient in view of economical reasons, the energy consumption can be reduced through better modeling techniques and control strategies. A popular `online' control strategy is model predictive control (MPC) that needs a good model of the system in order to predict and optimally excite the system. The goal is therefore to find a model of the distillation column that gives a good description of the

![Figure 31 Schematic representation of a binary distillation column.](image)
system and is not too computationally involved. A physical model of a distillation column is often too complex for 'online' simulation. Therefore, we want to find a relatively simple mathematical model of the distillation column, which is good enough to be used for MPC.

**Challenges in identification**

A distillation column can be considered as a multiple-input-multiple-output (MIMO) nonlinear system with drift (due to the changes in ambient temperature). Moreover, the distillation column is subject to long transients (due to large time constants of the system) and certain operation constrains.

We use simulated data of a binary distillation column model similar to [1]. A recently developed nonparametric identification technique, the so-called 'robust' Local Polynomial (LP) method [3], is used in combination with a (orthogonal) multisine excitation to preprocess the data. This gives us the best linear approximation (BLA) together with the error bounds of BLA for the distillation column, see Figure 32.

This analysis starts with the knowledge that the spectra satisfy:

\[
U(k) = U_0(k) + N_u(k) + T_{\alpha u}(\Omega_k) \\
Y(k) = G(\Omega_k)U_0(k) + Y_s(k) + N_y(k) + T_{\alpha y}(\Omega_k)
\]

where \(U\) and \(Y\) are the Fourier transforms of the input and output sequences, respectively, \(\Omega_k\) is the generalized frequency, \(G(\Omega)\) is the ny -by-nu frequency response matrix (FRM), \(N_u\) and \(N_y\) are the noise terms, \(Y_s\) is the zero mean stochastic nonlinear distortion, \(T_{\alpha u}\) and \(T_{\alpha y}\) are the transient terms of the system. In this case, \(G(\Omega)\) is the best linear approximation of the system, in mean square sense. The 'robust' LP method is used to locally approximate the transient terms and remove them [3].

![Figure 32 FRM estimation from a binary distillation column simulation using LP method. A non-parametric BLA of the frequency response estimate from the reboiler power input to the temperature at the top of the column output (x), the corresponding total variance on the estimate (-) and the variance due to the (simulation) noise.](image)

Multiple experiments with orthogonal multisine inputs are used to optimally excite the column [2]. Multisines are periodic signals, which in our case have the same amplitude and zero mean random
phase for each excited frequency, input and experiment. The `robust' LP method uses nu realizations per experiment, where the phases are orthogonal for the nu experiments.

Using the LP method we get BLA of the FRM of the distillation column. A simple parametric model is then estimated from this preprocessed data. This model can be used for the MPC to reduce the energy consumption of the distillation column.

References

2.3.3.11 Best Linearized models for RF systems
(Koen Vandermot)

Mathematical models are gaining importance in our every days life. In telecommunications, they are an enabling technology for the large and simultaneous increase of data bandwidths and battery life. This demanding requirements call for a whole new class of models that describe systems and components operating under extreme conditions. often, these techniques remain hidden for the end user, as their main role lies in the operation and the design of the portable devices. Up to now, these mathematical representations are extracted in a dual way: either the behavior of the device is over-simplified (mathematically the model is then called linear) and the accuracy of the model is inadequate, or a full physics-based model is used (mathematically the model is then non-linear). The latter alternative results in extremely accurate models, but is often practically intractable as it comes at the cost of a very high complexity and is resource hungry. In this thesis, we tried to combine the best of both worlds: provide models that have and acceptable level of accuracy, but remain easy to understand, to interpret and above all remain resource friendly. This new method opens the way for a whole new generation of enabling design tools for the manufacturing of tomorrows feature-rich portable telecom equipment.
2.4 TEAM D: MEDICAL MEASUREMENTS AND SIGNAL ANALYSIS (M2ESA)

2.4.1 Introduction to Medical Measurements and Signal Analysis (M2ESA)

Problem statement

Physicians have an enormous amount of practical experience which is most of the time based on old medical principles. The public opinion requires that diagnoses are accurate and infallible. To obtain this for all medical cases, the actual way of working which relies on experience becomes insufficient. Hence, a more robust, rigorous and well-founded approach is desired. Step by step, the medical world realizes the need and advantages of mathematical models in the quest for accurate diagnoses. Although the modeling science is a rather young part of science, the techniques which the modeling grocery has to offer are so abundant that without proper guidance one cannot see the wood for trees. This is the main reason why the medical community is rather reluctant to use the advanced modeling methods.

Objectives

In the M2ESA project, the measurement and modeling knowledge available at the department ELEC will be combined. The successful marriage between practice and theory offers the medical world simple, practical, risk-free and powerful tools to satisfy the users’ needs. A trade-off between theoretical/mathematical optimality and user-friendliness will be studied. Indeed, it is important that these emerging modeling techniques can be safely applied and interpreted by the layman user. Some of the projects that M2ESA focuses on, are the following:

- **Accurate oscillometric blood pressure measurements**: One of the most popular medical instruments used at home is the automatic non-invasive blood pressure meter (NIBP). Most medicine cupboards contain one and a lot of people use it on a daily basis. A cuff is wrapped around the arm of the patient and inflated until the circulation stops. Most classical automatic blood pressure meters are based on the oscillometric principle, which records the oscillations in the cuff pressure during deflation of the cuff. Out of this oscillometric waveform a mean arterial pressure (MAP) as well as a systolic and diastolic pressure is deducted by means of a mathematical algorithm. Each manufacturer of blood pressure meters, however, has developed his proper algorithm which is most of the time patented. On top of that, these algorithms are often not scientifically founded or transparent.

- **Non-invasive glucose measurements**: In the EU and US, 7.8% of the population have diabetes (www.diabetes.org), of which up to one third undiagnosed. Up to 20% of the population has a variable degree of glucose intolerance, and might also benefit from early glucose monitoring. Management of diabetes, in particular insulin-dependent forms, requires intensive control of blood glucose. Currently this is done by pricking the fingertip to draw blood and measure capillary blood glucose on an external sensor strip. This is a time-consuming, relatively painful procedure and offers only discontinuous monitoring. Developing a non-invasive glucose measurement procedure would be a considerable relief in the social, the physical as well as the financial field for these patients. Earlier attempts to
generate a similar application have failed due to the lack of a solid background on the measurement concept.

- **Functional Magnetic Resonance Imaging (fMRI):** MRI and fMRI is daily used to explore tumor tissue, infections, brain problems, muscles diseases, etc... Analyzing functional MRI data is often a hard task due to the fact that these periodic signals are strongly disturbed with noise. In many cases the signals are even buried under the noise and not visible, so that detection is quite impossible. In the past, different modeling approaches have been used without proper validation and comparison.

- **Vital signs of fetuses:** The premature mortality rate is still very high although the precaution and advances in the medical world. The current society puts a large responsibility on the shoulders of gynecologists. Therefore it is important to have proper access to the fetus’ vital signs. This is not only a major measurement challenge but also requires powerful signal analysis techniques. The main problem is that all non-invasive measurements are indirect, very noisy and on top of that nonlinear.

- **Breast cancer:** The actual detection of breast cancer, called mammography, is based on X-rays and is a very painful experience for the patient. New detection techniques based on low-power microwaves are emerging. The advantages are apparent: no breast compression, no ionizing radiation, no risk of heating the breast tissue. These new techniques can benefit from a strong signal analysis and modeling to reconstruct the images of interest.

### 2.4.2 Introduction to project MEMON

#### Problem statement

Wireless communication systems are widely available in our daily life, from mobile communications to cognitive radios and wireless ad hoc/sensor networks. In order to achieve a standard performance, more requirements are put on the radio frequency (RF) systems. Signals used in today’s wireless systems are characterized by high and fast dynamics in their envelope due to the use of sophisticated modulation techniques. Hence, they have large bandwidths and high peak-to-average power ratios. As a consequence, high requirements are put on the high power RF transmitters which are considered to be nonlinear systems and on the RF receivers whose digital bandwidths are limited due to shortage in high speed analog-to-digital converters, based on acceptable measurement accuracy.

One of the most important components in wireless communication systems is the radio frequency power amplifier (PA). Due to the high linearity and efficiency requirements, it is of the highest importance to accurately characterize the linear as well as the nonlinear behavior. Characterizing the linear behavior of RF components is a well known technique. However, characterizing the nonlinear behavior of these components is a completely different and more involved problem. The new high efficiency PA and transmitters, based on switched mode amplifiers, are emerging technologies that certainly require novel measurement methods.

#### Objectives

In this research project, excitation signals will be designed in order to reduce the requirements on the linear behavior of RF transmitters. New sampling and reconstruction strategies are developed
which allow measuring accurately wide-band waveforms based on relatively slow analog-to-digital converters.

Furthermore, the different measurement and modeling techniques that are nowadays available to analyze the nonlinear behavior of RF devices will be analyzed. A zillion methods have been published and used, but what is clearly missing is guidance for the user. This study will clarify why and how all these methods differ from each other based on either a system theoretical or stochastic point of view. Will all the different techniques be able to co-exist or is there a need for a new evolution?

This research is in collaboration with Prof. Niclas Björsell of the University of Gävle (Sweden) and is funded by a research grant of the Research Foundation-Flanders (FWO).

2.4.3 Short Description of the Research Projects of TEAM D

2.4.3.1 Functional Magnetic Resonance Imaging: an improved short record signal model
(Kurt Barbé, Wendy Van Moer and Lieve Lauwers)

Standard theories and methodologies are available to model time series and signals. This methodology is widely implemented in software packages. The only problem that this theory has in common is its validity for large record lengths. Most models have excellent ‘asymptotic’ properties. Unfortunately for small record lengths the theory can become untrustworthy and erroneous results may be encountered.

There is a rising number of applications where one has to deal with the problem that only a small number of measurements is available. In fMRI measurements the brain is scanned every 2-3 seconds and a sequence up to 100 scans is gathered, see [1]. The main reason for the short record of 100 measurements is due to the fact that a high resolution of the brain image is desired. The brain is split up into a number of voxels or volume element and this number is maximized with respect to the storage capacity of the scanner. A large number of voxels implies a short measurement record per voxel.

Although, there exist different modeling methodologies to handle fMRI measurements like neural networks, principal components analysis, support vector machines, etc... The standard modeling approach, commercially available, to handle fMRI-signals is 'Generalized Linear Model', [2], as discussed in Section II. Due to the short record lengths one is interested in small confidence sets around the unknown parameters of the model. The main objective is to assess the activation of the voxel under test. Statistically, the activation of the voxel is given by testing the magnitude of one of the parameters of the model with respect to the noise variance, [2]. In practice, one desires obtaining good confidence bounds on the magnitude of one of the parameters from the model and for the standard deviation of the noise.
In this study, we investigate how to construct these confidence sets for short record lengths. In the literature there exist three well-known confidence sets which are asymptotically equivalent and optimal: Wald's confidence set, Rao's confidence set and the Likelihood ratio confidence set. It is known however that the three methods reveal finite sample differences.

We explore different criteria to evaluate the confidence sets. Roughly, it is desired that (i) the confidence sets achieve the user-defined coverage probability, implying that the true unknown parameter is captured in the confidence set with the user-defined coverage probability. (ii) The confidence set is desired to be as small as possible. This implies that the number of false parameter values captured in the confidence set is as small as possible. These are the two standard evaluation criteria used in the literature. However, it is shown in that the smallest confidence set does not need to exist for a given problem. Hence, in practice criterion (ii) changes to the confidence set with the smallest expected size also known as the most accurate confidence set. The smallest expected size implies that one obtains the smallest confidence set averaged over different realizations of the confidence set. This paper is accepted for the IEEE Transactions on Instrumentation and Measurement.

References
2.4.3.2 Analyzing the Windkessel model as a potential candidate for calibrating oscillometric blood pressure measurements
(Kurt Barbé†, Wendy Van Moer‡ and Danny Schoors*)

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In the last decade automatic blood pressure meters have acquired their place in the family’s medicine-chest. On top of that, automatic blood pressure measurements have attracted the attention of the measurement community due to the challenge to understand the measurements. In particular, it remains a huge challenge to understand the relationship between the traditional Korotkoff method, used by physicians and the oscillometric method, used by automatic blood pressure meters. Both methods start the measurement by inflating the cuff wrapped around the patient’s arm. The cuff is inflated until the blood circulation stops followed by a slow deflation of the cuff until the systolic and diastolic blood pressures are determined. The fundamental difference between the Korotkoff and oscillometric method resides in the nature of the measured waveforms: the Korotkoff method implies an audio-wave obtained through the physician’s stethoscope where the oscillometric method is based on a pressure wave measured in the cuff. Besides this fundamental difference, the situation for the oscillometric method is complicated since the systolic and diastolic pressures are not measured but computed. Indeed, out of the measured oscillometry the maximum value is obtained from which the systolic and diastolic pressures are computed.

Although, the NIBP is commercially available, the medical world approaches the oscillometric waveform cautiously. The skepticism is founded by the non-transparent and/or non-scientific techniques. There exists no consensus on the algorithm to derive the systolic and diastolic blood pressure. The different algorithms are patented and their scientific principles are unknown. The commercial devices start by determining the Mean Arterial Pressure (MAP) defined as the maximum of the envelope of the oscillometric waveform. From the MAP value the systolic and diastolic pressures are derived. Roughly there exist two schools to compute the systolic and diastolic pressures from the MAP: the use of a height based criterion or the slope based criterion. The height based criterion states that the systolic and diastolic pressures are defined by fixed fractions of the MAP, where the slope based criterion defines the systolic and diastolic pressures as the closest points of inflexion to the left and the right of the MAP. Every automatic blood pressure meter enters a trial to compare the device with the Korotkoff method. The result of the trial awards the method with a quality label. This trial ensures that these blood pressure meters operate properly for the average patient but for severe hyper –or hypotension the device is considered untrustworthy. The main objective in current research on oscillometric blood pressure measurements is a calibration standard to accurately measure the blood pressure of patients suffering from hyper –or hypotension.
Since 2000 research with respect to blood pressure can be partitioned in: either gaining more insight in the physiological signals corresponding to the blood flow or improving the computation of the envelope of the oscillometric waveform. Recent additional insight in the fundamentals regarding blood flow and blood pressure is found in [21]: where the influence of the arm in blood pressure measurements was investigated; an investigation on the nature of the pulses in the cuff during a blood-pressure measurement campaign was performed in [22]; the blood flow was measured and modeled in [23]. The Windkessel model, [6], describes the relationship between the blood flow and the blood pressure. The relationship is expressed as a differential equation.

In this study, we propose a ‘data-based’ Fourier series analysis to describe the measured oscillometric waveform. The Fourier series approach follows from the linearization of the oscillometric waveform studied in. The Fourier series representation is used to calibrate the coefficients of the Windkessel differential equation and hence correct the NIBP’s computed systolic and diastolic blood pressure. The method is validated by a measurement campaign.

References

2.4.3.3 Automatic detection, estimation and validation of harmonic components in measured power spectra: all-in-one approach
(Kurt Barbé and Wendy Van Moer)

In various fields of applications one deals with the problem of either detecting harmonic components or assessing the absence of harmonic components in observed signals. Indeed, in spectrum analyzer and radar measurements, one is interested in detecting significant harmonic components. In functional magnetic resonance imaging (fMRI) measurements, one is interested in detecting tumor tissue based on a harmonic analysis of the data. In microwave measurements, it is interesting to detect only signal lines in order to avoid the need of calibrating all frequency lines. Time series analysis, like in modal analysis or power systems often operates under the assumption that no harmonic distortions are present in the data. It is in general important to assess the validity of this assumption to avoid biased models.

The simplest approach is a visual analysis of the signal’s power spectrum. For digital signals or time series the discrete Fourier transform can be applied to obtain the signals amplitude spectrum. For analogue signals the spectrum analyzer can be used to measure the signal’s power. If the signal-to-noise ratio is large enough the harmonic components leap out of the signal’s spectrum. Unfortunately, the signal-to-noise ratio can be small such that the visual approach becomes infeasible and time consuming.

Harmonic detection can be performed in both the time and the frequency domains. To the authors’ best knowledge, the time domain methods to detect harmonic components are generally based on a (multi)sine fitting approach, [7][8]. These parametric approaches have one drawback in common: obligatory user interaction. Most methods require at least the number of expected harmonics. The frequency domain methods are often by virtue of the wide application of the Fast Fourier transform non-parametrically,[9]. The advantage is that these require “almost” no user interaction. Besides that, these methods require minimal knowledge on the probability distribution of the disturbing noise.

Automatic detection criteria for harmonic components are often based on a statistical test. These methods provide no information beyond the detection of the spectral lines. No information is available on neither the probability of a false detection nor an estimate of the magnitude of the harmonic component.

Figure 35 Illustration of the philosophy of discriminant analysis: the spectrum analyzer measurements (gray), discrimination height (solid black line), average of the groups (dashed black lines), the standard deviation within groups (solid black arrows) and distance between the groups (dashed black arrow)
In this study, we offer a novel method based on a statistical test that automatically detects harmonics with the following advantages:

1. No user-interaction at all is needed and minimal postulated noise assumptions are required.
2. Every detected frequency receives a probability that the frequency is falsely classified as being either noise or a signal line.
3. The lines detected as signal lines receive an estimate of the magnitude of the harmonic component.

The detection algorithm can be implemented such that real time applications are allowed.

References


2.4.3.4 Estimating the amplitude of fMRI signals disturbed by Rician noise, using a Bayesian approach (Lieve Lauwers)

The goal of fMRI is to study and visualise brain activity upon stimulus for each volume element (or voxel) of the brain. The unknown parameter of interest is the amplitude of the fMRI signal since it is a measure of the voxel activity. In practise, the physician anatomically defines active regions of interest where he/she is interested in the intensity level of the brain activation.

In the following, we discuss our experimental results. For more information about the Bayesian estimation method, the reader is referred to [1].

In the considered fMRI experiment, the patient was in rest during the first ten brain scans. The following ten brain scans, the patient was asked to tap his fingers. This sequence was repeated four times, resulting in the fMRI paradigm. From the available data, we selected two voxels: one with strong activation (selected in the centre of the region of interest of the brain) and one with weak activation (selected at the boundaries of the region of interest). These two data sets are shown in Figure 36 (left) and (right), respectively (black lines). Due to minimal internal pre-processing of the data, the fMRI signal is expressed in arbitrary units (a.u.). Note that the number of data points per data set is very low ($N = 80$).

By visual inspection, we can clearly observe the underlying fMRI paradigm in the data from the left plot in Figure 36. However, we cannot at all recognise a square waveform in the data of the right plot. Nevertheless, weak activation has been confirmed by a physician for this data. In the following, we will verify whether the Bayesian approach can discover the intensity level of the voxel activation.
Experimental Results

In order to estimate the amplitude of the fMRI signals, a preprocessing step was performed using the prior knowledge of the rest and task phases in the fMRI paradigm. We inverted the 'rest' data to obtain a Rice distributed sequence with the same amplitude parameter over the brain scans [2]. In this way, the data can be processed at once. The negative data samples were discarded. The amplitude of the resulting Rice sequence is estimated using the Bayesian approach. To visualise the underlying fMRI paradigm from the estimated amplitude, this amplitude estimate is then multiplied by -1 for the rest period and +1 for the activation period.

For the Bayesian approach, the value for the parameter $\varepsilon$ was set to 1.1. The estimation results obtained for the strongly and weakly activated voxel are shown in the left and right plots of Figure [Figure 36], respectively. In these plots, the black line represents the measured fMRI signal and the full grey line represents the estimated fMRI signal. The transparent zones represent the 95% confidence bounds of the estimated amplitude.

We study the SNR since it is invariant to data scale changes. Furthermore, it is common practise to colour the image of the brain as a function of the SNR.

For the strongly activated voxel (left), the Bayesian approach obtains a $SNR = 1.47$. Note that the delay in the data (with respect to the underlying fMRI paradigm) can be explained by the brain dynamics: the brain is not capable of perfectly switching between the assignment and the resting phase. Ideally, these brain dynamics should be taken into account when slicing the data. This is a subject for future research. We simply used the transition points that were indicated by the physician.

For the weakly activated voxel, the Bayesian approach detects some voxel activity: the estimated SNR is 0.31.

To conclude, the above experimental results show that the Bayesian approach is able to quantify the level of voxel activity in active regions of the brain without any user interaction.


**References**


### 2.4.3.5 Development of advanced excitation signals and sampling techniques for improved RF system performance.

*(Charles Nader)*

Wireless communication systems are spreading widely in our daily life, with high expectations regarding speed and reliability based on today’s and future applications. As a consequence, high requirements are put on the radio frequency (RF) systems performance in order to achieve such expectations. Signals in today’s wireless systems are characterized with high and fast dynamics in their envelope due to the use of sophisticated modulation techniques. Hence, they are characterized by large bandwidths and high peak-to-average power ratios. As a result, high requirements are put on the RF transmitters, mainly the power amplifiers (PAs), which are characterized as nonlinear systems, and on the RF receivers whose digital bandwidths are limited due to shortage in high speed analog-to-digital converters, based on acceptable measurement accuracy.

The research work tackled the problems of shaping OFDM signals in order to improve the performance of today’s RF transmitters, and the problems of measuring and reconstructing wide-band waveforms based on undersampled data, which reduces the requirements on the digital bandwidth of today’s RF receivers.

### 2.4.3.6 1- Improving OFDM-based RF transmitter’s performance by shaping signals: Peak-to-Average Power Reduction and Digital Pre-Distortion.

*(Charles Nader)\(^{1,2,3}\), Per Landin\(^{1,2}\), Wendy Van Moer\(^{1}\), Niclas Björssel\(^{1}\), Peter Händel\(^{2}\)*

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A major challenge when using OFDM signals is the high peak-to-average power ratio (PAPR) that characterizes their envelopes. Such high PAPR causes clipping of the signal peaks when the RF power amplifier is operated at high power levels, i.e. compression region. Hence, in-band and out-of-band distortions are generated at the output of the PA, which deteriorate the system performance. As a consequence, the PA needs to be operated at lower power levels to avoid such distortion, i.e. back-off. However this results in a severe reduction of the PA efficiency. Two strategies exist to overcome this problem: reduce the back-off margin by PAPR reduction techniques, e.g. [1], or reduce the nonlinearity effects by pre-distorting the signal digitally (DPD), e.g. [2]. Combining both strategies, PAPR reduction and DPD, stands for high potential to increase
the power operating region of the PA, hence the efficiency, while keeping a fairly linear operating behavior.

![Figure 37 Test-setup used for digitally pre-processing the signal and measuring wide-band spectra](image)

The PAPR reduction technique used in this project is based on shaping the time domain signal by redistributing its energy in the frequency domain while satisfying constraints on the in-band error and out-of-band emission [1]. The reduction problem is formulated in a convex form and solved through an interior-point method [3]. The digital pre-distortion technique is based on reshaping the excitation signal by injecting a distortion extracted from an inverse model of the PA nonlinearity. As a consequence, the output signal from the PA will be linearly proportional to the input signal before the pre-distorter. DPD is achieved using the well-known parallel Hammerstein model with nonlinear order P and memory depth M. Measurements were conducted on a high power WLAN PA using a novel test-setup presented in Figure 37. Test cases where both digital processing techniques were used separately and combined were investigated.

Results have shown that reducing the PAPR and then pre-distorting the signal leads to a remarkable increase in the linear behavior as well as in the efficient use of the supplied DC power. Figure 38 presents an evaluation of the adjacent channel power ratio (ACPR), which stands for the ratio between the average power leaking to the adjacent channel and the average power in the main channel. Improvements in the order of 10 dB when comparing the use of both pre-processing techniques, labeled in the figure as 'reduced+pre-distorted', with respect to only using PAPR reduction, labeled in the figure as 'reduced', are remarkably seen. In addition, comparing the use of both combined techniques with respect to only using DPD, labeled in the figure as 'pre-distorted', shows an increase in the linear behavior margin of the same order as the PAPR reduction value.

![Figure 38 Adjacent channel power ratio evaluation](image)
Figure 39 presents an evaluation of the power added efficiency (PAE), which stands for the ratio of the difference between the output and input power of the PA over its drain supplied DC power. As shown, combining both PAPR reduction and DPD will allow an increase in the efficient use of the DC supplied power in the order of 20%, with respect to only using DPD.

An important issue that needs further investigation is the DPD behavior and its stability at high power levels. Both figures show deterioration in the DPD performance when reaching a certain strong compression point. The reason is linked to the increase in the PAPR at the output of the DPD in order to model an inverse effect of the PA strong linearity. Such behavior is unrealistic as it will break the PA input stage. A strategy to improve the stability margin of the DPD is to apply PAPR reduction at its output without deteriorating the performance of the DPD.

2.4.3.7 2-Harmonic sampling and reconstruction of wide-band undersampled data
(Charles Nader¹,²,³, Wendy Van Moer³, Kurt Barbé³, Niclas Björsell¹, Peter Händel²)

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The secret behind a successful harmonic sampling of wide-band waveforms is revealed. It is a novel tool to reconstruct wide-band waveforms from undersampled data. Choosing a sampling frequency with an irrational property will assure an overlap-free spectrum and eliminate the probability of having ambiguities in tones standing on multiples of Nyquist frequency. In practice, such irrational property can be relaxed based on some appropriate number of decimals. Indeed, working at RF scale with frequency accuracy down to 1 Hz, will allow the use of a sampling frequency with an irrational property. In addition, a road-map to find the aimed sampling frequency with an optimal number of samples is presented. It satisfies the coherent condition of sampling and offers a reduced requirement on the data usage and processing time, based on a good accuracy.

Turning the problem of harmonic sampling around, having a spectrum free from overlapping bins, the original wide-band spectrum can be reconstructed by a descrambling algorithm. Hence, a wide-band time domain waveform can be reconstructed from undersampled data and used for advanced digital processing. Both harmonic sampling and reconstruction of wide-band undersampled data were validated through simulations which mimic real measurement conditions, Figure 40 & Figure

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Figure 39 Power added efficiency evaluation
An accurate reconstruction of the undersampled spectrum was achieved with a reconstruction error comparable to the level of the noise floor.

References


2.4.3.8 A bottom up approach to non-invasive glucose measurements

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1. Introduction

There are 150 millions of Diabetic Patients around the world and the World Health Organization expects 300 million by 2025. The intensive insulin therapy (i.i.t) improves the conditions and prognostic of the patient but increases the risk of hypoglycaemic events [1]. Therefore, close monitoring of glucose is highly recommended such that the level of glucose can be kept as close as possible into the normal range. Actually the standard for home monitoring is based on a finger-prick blood samples procedure which is time-consuming, painful and offers only intermittent samples.
Developing a non-invasive glucose measurement procedure would be a considerate relief: social, physical and would improve the glucose monitoring as required by the i.i.t. Earlier attempts to generate a similar application have failed, or they have not achieved the technical or clinical requirements; due to the lack of a solid background on the measurement concept, poor use of information and data processing, or have not taken into account external factors that could affect the sensor behaviour [2][3].

This project will focus on the development of a non-invasive glucose measurement procedure based on bio-impedance measurements, which are well-known in electrical engineering. The impedance value at the frequencies where glucose molecules resonate is proportional to the glucose level in the blood. This knowledge combined with strong signal analysis tools, oriented to isolate the blood glucose (BG) signal, will generate a realistic and workable glucose measurement concept. The development of a non-invasive system will be developed following the framework to conduct Electric Impedance spectroscopy experiments [4] (Figure 42)

2. Measurement technique

Phase 1. Collecting experimental data: The experiment design will be oriented to the development of a sound glucose detection and calibration algorithm, which is the principal problem in the development of glucose monitoring systems. Therefore the frequency band in which the glucose influences the impedance will be determined through representative, increasingly complex alternatives. (i) cell culture media, (ii) human plasma, (iii) human blood, (iv) on human skin.

Phase 2. Data Analysis: The first stage in the data analysis consists of identifying the frequency bands that are influenced by a varying glucose concentration. Note that this was not always properly done in former investigations; different works report contradictory results [5]. On top of that, it is necessary to examine how these frequency bands vary as a function of the medium, the volume of the measurement cell, the temperature and other chemical components present in the test medium. The interaction together the environmental influence will look like noise.

Phase 3. Modeling: This will be done by using a parametric model, which has the advantage that the glucose level can also be validated. The most commonly used parametric estimator is the Maximum Likelihood estimator (MLE). This estimator has good statistical properties if a sufficiently large number of data points are available. For most medical applications, however, only a limited
number of experiments can be performed. As a result, the robustness of the MLE needs to be verified for short data records.

3. Sensor hardware

During the different measurement steps different experiments will be registered and this will allow the progressive development of the system. We will consider the appropriate configuration of the sensor, its size, comfort, environmental effect, lag, offset and other technical and clinical considerations previously discussed in literature [6].

4. Conclusions

The most important findings and products within the framework of this project are: The identification of the impedance behaviour of glucose and its effects on blood components. Algorithms oriented toward the separation of glucose-related information from the noise, including the nonlinearities presents in the glucose impedance behaviour. This completed with a calibration algorithm oriented to clinical calibration given the intra and inter patient variability. The ultimate aim is a complete non-invasive continuous glucose monitoring system.

References


2.4.3.9 Linearizing oscillometric blood pressure measurements: (non)sense? (Wendy Van Moer and Kurt Barbé)

One of the most popular medical instruments used at home is the automatic non-invasive blood pressure meter (NIBP). Most medicine cupboards contain one and a lot of people use it on a daily basis. A cuff is wrapped around the arm of the patient and inflated until the circulation stops. Most classical automatic blood pressure meters are based on the oscillometric principle, which records the oscillations in the cuff pressure during deflation of the cuff. Out of this oscillometric waveform a
mean arterial pressure (MAP) as well as a systolic and diastolic pressure is deducted by means of a mathematical algorithm. Each manufacturer of blood pressure meters, however, has developed his proper algorithm which is most of the time patented. On top of that, these algorithms are often not scientifically founded or transparent.

During an oscillometric blood pressure measurement the complete oscillometric waveform is measured. Up till now in most cases, the only information used from this waveform is the maximum of the associated envelope, i.e. the mean arterial pressure, and some deducted values as the systolic and diastolic values. The remaining part of the information that is hidden in the measured oscillometric waveform is thrown away simply due to the fact that no interpretation of the full content of the waveform is available. Hence, the main focusing point of present research on blood pressure measurements lies in establishing the relation between the mean arterial pressure and the systolic and diastolic pressure. Two main schools can be distinguished: the height-based and the slope-based school. The height-based school uses a fixed, patented ratio of the height of the MAP to define the systolic and diastolic pressures. On the other hand, the slope-based school uses the points of inflection of the envelope to define the systolic and diastolic pressure. Both algorithms rely on an accurate determination of the envelope of the oscillometric waveform. In many cases the oscillometric waveform has no clear envelope and determining the maximum is rather difficult and far from being accurate.

In the mid-90’s research regarding automated blood pressure meters focused mainly on determining the relationship between the systolic or the diastolic pressure and the MAP. Since 2000 research with respect to blood pressure can be partitioned in: either gaining more insight in the physiological signals corresponding to the blood flow and improving the computation of the envelope of the oscillometric waveform. Additional insight in the fundamentals regarding blood flow and blood pressure is found in [21] where the influence of the arm in blood pressure measurements was investigated; an investigation on the nature of the pulses in the cuff during a blood-pressure measurement campaign was performed in [22]; the blood flow was measured and modeled in [23].

In this project a user-friendly and transparent method to determine the systolic and diastolic blood pressure is proposed, based on a frequency domain signal processing approach. This method consists of linearizing the oscillometric blood pressure waveform. Doing so results in a much smoother envelope of the oscillometric waveform. This paper investigates whether or not this ‘linearized’ envelope is sufficient to accurately calculate the systolic or diastolic blood pressure. Or in other words, does this linearized approach contain as much information as the Korotkoff method?

Therefore a measurement campaign was setup in which the blood pressure of 75 patients was measured by means of the Korotkoff method as well as the commercially available automatic blood pressure meter. In a second step the measured oscillometric waveforms are linearized. Based on this linearization, the systolic and diastolic blood pressures are computed. This is done by using a
height-based algorithm. The results of the Korotkoff method, the commercial NIBP and the linearized method are compared and analyzed.

A first step is taken to develop a more accurate algorithm for automatic blood pressure meters. Based on the Fourier representation of the measured oscillometric waveform, more insight is gained in the information present in the oscillometric waveform. We showed that the blood pressure measurements are subjected to nonlinearities with respect to the signal carrier. A simple approach to remove the nonlinearities from the measurements by a frequency domain method is proposed. The corresponding time-domain waveform is defined as the ‘best’ AM-signal approximation of the measurements. Based on the best AM-signal approximation a user-friendly and transparent method to determine the mean arterial pressure is obtained. The approach has been validated with statistical tests.

References

2.4.3.10 Mirrored parallel Hammerstein predistortion for multitone generation (Kevin Voet, Peter Händel, Niclas Bjorsell, and Wendy Van Moer)

2 Center for RF Measurement Technology, University of Gävle
3 Signal Processing Lab, Royal Institute of Technology, Stockholm

The evolution of digital signal processing enables cost-efficient trade-offs between performance boosting by digital operations and cost-reduction by reducing the requirements on the analog hardware. In this work, the authors consider digital predistortion of radio frequency vector signal generators (VSGs) by means of parametric frequency-dependent modeling of the inverse of the nonlinear artifacts, including artifacts from in-phase (I) and quadrature (Q) modulation, leakage from the local oscillator (LO), and power amplifier. The approach taken here is a dynamic joint compensation of IQ impairments, LO leakage, and power amplifier non-linearities. A recursive implementation of this method is considered in [1]. In [2], a dynamic joint scheme was proposed for combating the impairments in direct conversion radio transmitters. One purpose of this study is
to investigate the potential of such dynamic predistortion for improving performance of the VSG. A arbitrary digital waveform baseband test stimuli $z_n$ (a complex-valued quantity) was generated by the personal computer (PC) software and sent in its digital format to the VSG for digital-analog conversion of the I and Q branches, followed by an IQ-modulation producing the analog radio frequency signal $r_t$. Here, and in the sequel, $t$ denotes the absolute time (in seconds, that is $[s]$), and $n$ its time-discrete counterpart, related by the sampling frequency $F_s [s^{-1}]$ of the set-up. In the calibration set-up, the radio frequency output $r_t$ of the signal generator was directly connected to a vector signal analyzer (VSA), producing the down-converted baseband representation $s_n$ of the radio frequency signal. The objective of this work is to produce a high quality radio frequency output $r_t$ by designing a digital predistorter that calculates the proper stimuli $z_n$ by nonlinear filtering of a base-band reference $r_n$, according to a least-squares figure of merit. In other words, $r_n$ was the desired baseband representation of the radio frequency signal $r_t$, and $z_n$ the digital input to the VSG producing it.

The results show that the proposed method makes an obvious impact on the VSG performance. After predistortion, the mirror-frequency interference decreased by approximately 8 dB on the average (min 6.0 dB and max 13.7 dB), and the LO leakage by 17 dB; the improvements in inter-modulation products were in the region of 6 dB.

References
2.5 TEAM E: IDENTIFICATION OF BIOGEOCHEMICAL SIGNALS & SYSTEMS (IBISS)

2.5.1 Introduction to Team E

The long term goal of this team is to build measurement based models for environmental systems. The current trend is to build more complex models in order to simulate the ‘real’ world, while a ‘good’ model is not necessarily the most complex model. On the contrary, it only needs that complexity, which is supported by experimental measurements. It has to be able to describe all significant variation in the data, without modelling the stochastic measurement uncertainties. These models are used for two purposes: (i) to extract the maximum amount of significant information out of noisy measurements; (ii) to make future predictions.

Suppose, for instance, that we have a climate model with a set of estimated parameters and an experimental record. Now, I would like to bring in an additional physical process, which would make the model more realistic. What will happen?

With every modelled process, some model parameters are associated. Tuning these parameters will match the extended model better on the record. So, our model has become more realistic. However, uncertainties are associated with these additional model parameters and these additional uncertainties will lower the prediction horizon of the model. So, a higher complexity could be a disadvantage for a model. Briefly, a first step in the search for a good climate model is the determination of its complexity. To reach this goal, the modeller needs the experimental data.

On the other hand of the spectrum, experimentalists are measuring climate/ ecological changes in the past. However, the past cannot be directly measured. Instead, proxies in sediments, biogenic carbonates, ice cores etc…. are measured and consequently, the history is revealed as function of a distance, while we would like to have a time series. The latter can be introduced by comparing the measured record with a model, containing the time. The simplest models can be 14C-dating curves, but any model containing time can do the trick. So, at this stage, every experimentalist will need models and modellers and some evident questions arising are: which model to choose? How are the model parameters tuned (on a record, not yet dated or on a previously dated one)? How are errors propagating thorough this interaction between models and measurements?

These two examples show that a horizontal orientated approach, with specialists in measuring and others in modelling, has its limits. For this reason, we have chosen to approach some important questions in environmental reconstruction and prediction in a vertical manner, where we follow the information stream from the bottom up, from the experimental set-up, the calibration of the instrument, dating the records, over tuning the model parameters, till the selection of the appropriate model. Such a quantitative formulation of the measurement problem is precisely what has been developed in the system identification community and our first short term goal is the introduction of this approach in the community of environmental sciences.
2.5.2 Short description of the research projects of team E

2.5.2.1 Nonlinear And Dynamical Models For Temperature Reconstructions From Multi Proxy Data In Bivalve Shells
(Maite Bauwens)

A shell may reveal past climatic information, this is possible because shells live in equilibrium with the environment. The chemical composition of a shell depends on environmental variables such as temperature, rainfall, and food availability... the difficulty however, is the translation of the chemical signals that can be measured along a shell’s growth axis into environmental information.

Most studies in this field try to find one to one relationships between a chemical element (=proxy) and an environmental parameter based on the similarity of the two seasonal patterns. However, the incorporation of chemical elements in a shell appears to be highly complex, and is mostly influenced by several environmental parameters at a time.

In this work we propose a so called multi-proxy approach. We describe the behavior of one environmental parameter (e.g. temperature) by using a combination of chemical elements (e.g. Mg, Sr, Ba and Pb). The main advantage of this multi-proxy approach is that unexplained variations in one proxy (e.g. Mg) can be explained by variations in another proxy (e.g. Sr) without fully understanding the origin of these variations.

Along this work it becomes clear that many elements show nonlinear relationships with their environment. Therefore the multi-proxy approach is applied to nonlinear models. In a second step we introduce (linear and nonlinear) dynamical multi-proxy models, in order to deal with possible deleted proxy incorporation during the shell formation. The introduction of dynamics results eventually in the best reconstructions. The best temperature reconstructions are obtained by dynamical Mg models that result in reconstructions with an average error of 1.3°C. This is considerably better than the reconstructions obtained by classical Mg models that show average errors of 4.2°C.

2.5.2.2 Improved climate reconstructions with a parametric method for time-series reconstruction with the averaging effect taken into account
(Veerle Beelaerts)

Arctica islandica has a great potential as climate archive because it is an extremely long-lived bivalve and consequently can provide century long environmental records. With the oxygen isotopic composition in marine bivalve shells the sea water temperature can be reconstructed from the period the shell lived. Carbonate samples for the determination of the oxygen isotopic composition are generally collected by milling a portion from the shell along its major growth axis, with a micro-mill. Usually the volume of these milled samples is kept constant, though shell growth rate decreases with age. At age 20 the yearly increment widths of A. islandica shells decrease to about 1 mm and even lower. At a certain point, the width of the sample, here 300 μm, will represent a large fraction of the yearly increment width and therefore, averaging errors are likely
to occur. These averaging errors are detected and corrected with the method described in Beelaerts et al. (2010).

From the oxygen isotope data which are corrected for averaging, temperature is reconstructed with an equation defined by Grossmann and Ku (1986):

$$T_{\delta^{18}O}(^\circ C) = 20.60 - 4.34[(\delta^{18}O_{\text{aragonite}} - (\delta^{18}O_{\text{seawater}} - 0.20)]$$  \hspace{1cm} (5.2)

with $T_{\delta^{18}O}(^\circ C)$ the temperature reconstruction, $\delta^{18}O_{\text{aragonite}}$ the oxygen isotope value of the shell, and $\delta^{18}O_{\text{seawater}}$ the oxygen isotopes value of the seawater.

The results are compared to instrumental sea surface temperatures. In Figure 45, the instrumental temperature data, $T(^\circ C)$ (full light gray line) were compared with the temperature data derived from raw $\delta^{18}O$-record, $T_{\delta^{18}O_M}(^\circ C)$ (dashed dark gray line) and the temperature data derived from the corrected $\delta^{18}O$-data, $T_{\delta^{18}O_C}(^\circ C)$ (full black line). $T_{\delta^{18}O_C}(^\circ C)$ gives significantly better results than $T_{\delta^{18}O_M}(^\circ C)$ when compared with $T(^\circ C)$.

Figure 45 The instrumental temperature record (full light gray line), the temperature record derived from the measured $\delta^{18}O$ (dashed dark gray line) and the temperature record derived from the corrected $\delta^{18}O$ (full black line) as a function of the calendar year

References


2.6 SPIN-OFF: NMDG Engineering

Contact Person:
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Director
email: marc.vanden_bossche@nmdg.be

2.6.1 Vision

NMDG is committed to becoming the market leader in “next-generation characterization and analysis tools” for the high-frequency electronics and communication market. Secondly NMDG wants to be the preferred partner of test engineers who need to improve and accelerate their design and test processes, yet face the challenges of non-linear component behaviour.

In order to change the design and test paradigm, NMDG is developing, selling and supporting next-generation products focused on fast, complete and accurate characterization and analysis of high-frequency active and high-speed digital components. These products combine existing instruments with new hardware supported by reliable and easy-to-use software, while being fully integrated with the customer’s processes. To anticipate the ever-growing complexity of design, the need for realistic models and in order to eliminate the effect of the measurement set-up on product specifications, these products will be seamlessly combined with simulation tools.

2.6.2 At a glance

NMDG is a young, dynamic high-tech company offering next-generation characterization and analysis tools and services to a wide range of customers in the high-frequency electronics and communication market. NMDG provides these customers a competitive advantage by reducing development time and cutting test costs while improving yield and reliability.

Leveraging the experience of a team of highly qualified high-frequency measurement and simulation technology professionals, NMDG is presently focusing on four revenue generators: products, characterization services, measurement-based behavioural modelling services and system integration services.

A close and personalized interaction with the customer is of paramount importance to NMDG.

2.6.3 Markets

The markets covered by NMDG solutions reach from “sand” to “system” and correspond to the markets that were penetrated by the S-parameter measurement capability.

“From Sand”

Using realistic and complete measurement information, provided by the NMDG products and services, semiconductor manufacturers can verify, improve and certify their large-signal models,
before releasing their design kits. This is a guarantee for design cycle reduction. By gaining complete insight in the behaviour of their transistors through the extension of their present source- and load-pull systems with measurement capabilities from NMDG, power amplifier designers and manufacturers can achieve new performance levels with their components. Also, using the products of NMDG in combination with the proper tuner solutions, source- and load-pull measurements become a matter of minutes increasing the throughput of testing components.

"To System"

By extending vector signal generator – analyser set-ups with the NMDG products, it is possible to characterize and analyse single-ended and differential devices, possibly in a non- 50 Ohm environment.

Amongst others, measurement-based behavioural models can be created for chip manufacturers improving the simulation accuracy and reducing model uncertainty in the design cycle.

Finally, NMDG is convinced that its products will play an important role in the high-speed digital market place as it adopts future RF techniques.

2.6.4 Products and Services

Based on accurate characterization of HF active components under realistic conditions, the NMDG solutions streamline the R&D development and test processes, which result in:

- High measurement accuracy and efficiency
- Faster designs and testing
- Significant cost savings

2.6.5 Large-Signal Network Analyser Products together with Maury Microwave

The MT4463, a product sold worldwide by Maury Microwave and empowered by NMDG, characterizes the non-linear behaviour of RF, microwave and fast analogue switching components in a network analyser sense, based on large-signal network analyser technology. The MT4463 goes beyond pass/fail tests where classic measurement approaches fail to give insight. The instrument aids in understanding what occurs at the component level under near realistic circumstances.

The large-signal network analyser measures the complete voltage and current or incident/reflected wave behaviour under small- (Sparameters) and large-signal conditions. Independent of the type of component, from transistor to system, a one-tone or periodic modulation can be applied under mismatched conditions while the complete behaviour is measured and represented in different ways.
In contrast to the almost complete measurement capabilities of the MT4463, the VNAPlus, also presently sold worldwide through Maury Microwave, is an entry-level add-on kit for Agilent PNA’s to provide it with complete harmonic characterization capability.

Both the MT4463 and the VNAPlus can be combined with the Maury tuners and the Maury Automated Test System (ATS) software to operate in a non-50 Ohm environment.

2.6.6 Characterization Service

Make sure your transistor libraries pass the "design test" using certified design kits.

The NMDG characterization service enables the user to explore the capabilities of a largesignal network analyser without having to invest in the MT4463 and VNAPlus.

The NMDG characterization service allows to:

- Study the true and complete high-frequency behaviour of components under realistic large-signal RF excitation and mismatch conditions
- Eliminate the uncertainty of the impact of the measurement environment
- Investigate the reliability of components under realistic high-frequency conditions
- Reduce the design time by making sure that the designers use LSNA-certified models

Also available are:

- Hot S-parameter measurements
- Stability analysis under hot conditions
- Measurement of impedance of sources, oscillators under hot conditions
- Conversion matrices
- Characterization of frequency translating devices, e.g. mixers
- In-circuit measurements using high-impedance probes

2.6.7 Measurement-based Behavioural Modeling Service

Simulate your active HF components under mismatched conditions fast and accurately.

The Standard Service includes:

- Extraction of a measurement-based behavioural model at the specified fundamental frequency for a given input power range and a range of termination impedances
- Predicts the complete voltage - current or incident - reflected wave behaviour at the input and output port of the component, taking into account the effect of source and load impedance
  - The bias circuitry is assumed to be part of the component
  - Modulation prediction is possible under quasi-static assumption
  - Connection into ADS from Agilent Technologies
  - Components can be connectorised, in fixture (incl. de-embedding) or on wafer
Through customization of the measurement set-up and adaptation of the algorithms, it is possible to extend the behavioural model with some harmonic information and to analyse the effect of memory effects through the bias circuitry.

NMDG also provides services to connect measurements into different simulation environments and to integrate them in the design process.

2.6.8 HF Measurement System Consulting

NMDG extends your measurement set-ups or develops set-ups beyond the capabilities of regular instrumentation to characterize and analyse active HF components in R&D and test environments.

The customer benefits from NMDG’s unique expertise in HF active component characterization, instrument control, algorithm and GUI development.

NMDG’s expertise takes away the burden to develop, adapt and support measurement systems, and makes sure that your engineers stay focused on design and manufacturing.

2.6.9 LSNA History

Large-signal network analysis (LSNA) provides complete and accurate characterization of non-linear devices under realistic operating conditions using one measurement set-up with a single connection.

These measurements reveal device characteristics which could not be seen before with other commercially available equipment.

The technology provides a step-by-step analysis of the device behaviour with increasing signal complexity, to qualify and improve transistor models and improve system level designs. The large-signal network analysis technology specifically addresses the non-linear large-signal measurement needs of the semiconductor R&D and manufacturing customers to characterize amplifiers, transistors and other active components in cell phones, base stations and aerospace/defence equipment.

Many years of research work by the Hewlett Packard and later Agilent NMDG team at Agilent Technologies in cooperation with different research institutes led to what LSNA technology is today.

Under license from Agilent Technologies, the technology resulted in the commercial realization of the MT4463. This product is currently produced and sold worldwide by Maury Microwave with the help of NMDG. The latter also provides presages, installation and post sales support while continuing development of future generations.
2.6.10 About NMDG

NMDG’s ground breaking technology had its origins at the department ELEC of the Vrije Universiteit Brussel in the early nineties when some employees took part in the creation of the large-signal network analyser technology at that department. The concepts and processes to calibrate and measure non-linear high-frequency active components have earned a worldwide recognition.

In order to offer better, more complete products NMDG continues its research and development via partnerships and co-operation with leading academic and research institutes.

In July 2006, NMDG attracted an important research grant from the Flemish government through an IWT project. This helped the initial acceleration of the company.

During the summer 2007 a venture capital seed funding enables the company to accelerate its own product development plans, including research and development of large-signal network analysis tools for RF, microwave and high-speed digital components. This will also allow expanding its commercial team while strengthening relationships with its customers and partners.

For further information, please visit us at: www.nmdg.be
3. Education

3.1 THE INTRODUCTION OF THE BACHELOR-MASTER STRUCTURE

Since the academic year 2004-2005 the “bachelor - master” structure (replacing the candidate - licentiate structure) has been introduced. The initiative for this thorough interference in the programmes of higher education was the Bologna Declaration. The Ministers of Education of 31 European Countries gave in 1999 the start to uniform the higher education in Europe. Although the Bologna process creates convergence, the fundamental principles of autonomy and diversity are still respected. The aim of the Bologna Declaration is to improve in Europe the exchangeability of degrees, the free mobility of students, quality assurance and a flexible study package by introducing credit systems.

3.2 COURSES LECTURED IN THE FACULTY OF ENGINEERING

3.2.1 Lectures and practical courses

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<td>gevorderde controletechnieken - Prof. R. Pintelon – Prof. Jan Swevers (KUL)</td>
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<td>3rd year Electronic and IT Engineer (optional)</td>
<td>4</td>
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<tr>
<td>Navigatie en intelligente voertuigen - Prof. L. Van Biesen</td>
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<tr>
<td>Navigation and Intelligent Vehicles</td>
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<tr>
<td>2nd Master of Applied Sciences and Engineering: Electro-Mechanical Engineering (compulsory)</td>
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<tr>
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<tr>
<td>Physical Communication - Prof. L. Van Biesen</td>
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<td>1st Master of Applied Sciences and Engineering: Computer Science (optional)</td>
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<td>2nd Master of Applied Sciences and Engineering: Computer Science (optional)</td>
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<tr>
<td>3rd year Electronic and IT Engineer (compulsory)</td>
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<td>Signaaltheorie - Prof. L. Van Biesen</td>
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<td>Signal Theory</td>
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<td>2nd Master of Applied Sciences and Engineering: Computer Science (optional)</td>
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<tr>
<td>2nd Master of Applied Sciences and Engineering: Photonics Engineering (optional)</td>
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<td>3rd year Electronic and IT Engineer (compulsory)</td>
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<td>Lectures and practical courses</td>
<td>Credits</td>
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| **Stage: elektrotechniek - Prof. L. Van Biesen**  
Traineeship: Electrical Engineering |         |
| 2nd Master of Applied Sciences and Engineering : Applied Computer Sciences (optional) |         |
| 2nd Master of Applied Sciences and Engineering : Biomedical Engineering (optional) |         |
| 2nd Master of Applied Sciences and Engineering : Electronics and IT-Engineering (optional) |         |
| 3rd year Electronic and IT Engineer (optional) | 6       |
| **Stem, beeld, navigatie en telemetrie - Prof. L. Van Biesen**  
Voice, Image Coding, Media and Systems |         |
| 1st Master of Applied Sciences and Engineering: Computer Science (optional) (optional) |         |
| 2nd Master of Applied Sciences and Engineering : Electronics and IT-Engineering (optional) |         |
| 2nd Master of Applied Sciences and Engineering: Computer Science (optional) |         |
| 2nd Master of Applied Sciences and Engineering: Photonics Engineering (optional) |         |
| 3rd year Electronic and IT Engineer (optional) | 6       |
| **Toegepaste elektriciteit - Prof. L. Van Biesen, Prof. Wendy Van Moer**  
Basic Electricity |         |
| 2nd Bachelor of Applied Sciences and Engineering (compulsory) |         |
| 3rd Bachelor of Applied Sciences and Engineering (compulsory) | 7       |
| **Transmissiemedia en -systemen - Prof. L. Van Biesen**  
Physical Communication |         |
| 2nd Master of Applied Sciences and Engineering : Electronics and IT-Engineering (optional) |         |
| 2nd Master of Applied Sciences and Engineering: Photonics Engineering (optional) |         |
| 3rd year Electronic and IT Engineer (compulsory) | 4       |
| 2nd Master of Applied Sciences and Engineering : Applied Computer Sciences (optional) | 6       |
| **CAE-tools voor het ontwerp van analoge elektronische schakelingen - Prof. G. Vandersteen**  
CAE-tools for the Design of Analog Electronic Circuits |         |
| 2nd Master of Applied Sciences and Engineering : Electronics and IT-Engineering (optional) |         |
| 2nd Master of Applied Sciences and Engineering: Photonics Engineering (optional) |         |
| 3rd year Electronic and IT Engineer (optional) | 4       |
| **Design en karakteriseren van hoogfrequente (niet-lineaire) systemen - Prof. W. Van Moer**  
Design and Characterisation of RF and Microwave Nonlinear Systems |         |
| 2nd Master of Applied Sciences and Engineering : Electronics and IT-Engineering (optional) |         |
| 2nd Master of Applied Sciences and Engineering: Photonics Engineering (optional) |         |
| 3rd year Electronic and IT Engineer (optional) | 4       |
3.3 MINOR “MEASURING, MODELLING, AND SIMULATION OF DYNAMIC SYSTEMS” OFFERED WITHIN THE 2ND MASTER ELECTRONICS AND INFORMATION TECHNOLOGY

<table>
<thead>
<tr>
<th>Course (Dutch or English)</th>
<th>Credits</th>
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<tr>
<td>An introduction to system identification - Prof. J. Schoukens</td>
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<tr>
<td>Measuring and modelling of nonlinear systems - Prof. J. Schoukens</td>
<td>4</td>
</tr>
<tr>
<td>Industrial measurement environments - Prof. L. Van Biesen</td>
<td>4</td>
</tr>
<tr>
<td>Identification of dynamic systems - Prof. R. Pintelon</td>
<td>4</td>
</tr>
<tr>
<td>Advanced control methods - Prof. R. Pintelon - Prof. J. Swevers, KULeuven</td>
<td>4</td>
</tr>
<tr>
<td>CAE-tools for the design of analog electronic circuits - Prof. G. Vandersteen</td>
<td>4</td>
</tr>
<tr>
<td>Design and characterization of high-frequency (nonlinear) systems - Prof. W. Van Moer</td>
<td>4</td>
</tr>
<tr>
<td>Bio-informatics and datamining - Prof. J. Schoukens - Prof. Y. Moreau (KULeuven)</td>
<td>4</td>
</tr>
</tbody>
</table>

Design of new systems and products is a complex process with a central role for the engineer. A good physical insight is combined with experimental results to come eventually to the best products (lowest price, good quality, no pollution) to concur the competition. Each step in this design process requires dedicated tools. We should collect good experimental data, often collected under poor conditions (course: Industrial measurement techniques). From these measurements a wide variety of models is extracted for the designer (course: Identification of dynamic systems) that should meet many requirements. Sometimes the models are used in simulation tools like ‘Spice’, or they are used to measure parameters that are difficult to access directly, like the damping of a wing, the time constants of an electrical machine. Models are also at the basis of control design (for example the active suspension of a car). A lot of commercial software packages are available on the market to support the design process, but using these tools without understanding can result in a bad or poor design or even create dangerous situations. In a simulation package, many user parameters are set to default values that are not always suitable for the specific situation, and this can jeopardize the results completely (course: CAE-tools for the design of analog electronic circuits). During the design, it is very tempting to rely on linear models because they are very intuitive, easy to use, many rules of thumb are available, and it is not too difficult to extract them from measurements. However, nature is not linear. What is the quality of the design under these conditions? Is the stability analysis of the controller still valid? How to design a controller in the presence of nonlinear distortions? How is the bit-error-rate of a high speed communication link affected by a nonlinear amplifier? The courses Measuring and modelling of nonlinear systems and Advanced control methods help to answer these questions. These ideas are practically applied in microwave designs where transistors are often pushed in their nonlinear operating region for power efficiency reasons (course: Design and characterization of high-frequency (nonlinear) systems). As an engineer, we are overwhelmed with information that is often out of the scope or our interest. The course on Bioinformatics and datamining opens a new
scientific field that is directed to the problem how to extract the desired information out of enormous amounts of data. How can we turn data into information?

3.4 WORKSHOP INFORMATION AND COMMUNICATION TECHNOLOGY ("ICT")

A workshop named "ICT" has been introduced in the fourth semester of the Bachelor of Engineering at the Faculty of Engineering VUB. It is the consequence of the introduction of a Bachelor-Master structure into our old european “Polytechnic School” engineering education structure.

At VUB, the bachelor programme, which counts 6 semesters, is identical for all the engineering students except that semesters 5 and 6 are specific to the speciality they choose.

Several workshops illustrating these specialities have been introduced in the semester 4 during the academic year 2002-2003. One of them is the "Workshop ICT".

Prof. Jacques Tiberghien (Dept. INFO) and Prof. Alain Barel (Dept. ELEC) are the promoters of the new workshop and with the help of the technical and academic staff of the Dept. INFO, ELEC and ETRO, the workshop have been designed and run for the first time between February and May 2003.

3.4.1 The task.

Design the control of a water tower as a “project based learning” pedagogy.

A water tower is a very simple installation which delivers drinking-water to the inhabitants of a town through a distribution network [Figure 46]

It is obvious that building a large water tower brings two advantages: the distribution is passive, i.e. it continues to work even when there is no more electric power available and the distribution pressure shows only small variations with the volume of water left in the tower.

The owner or the operator of the water tower must manually or preferably automatically care to keep the level of water in the water tower as constant as possible in spite of the fluctuations on the
flow of water imposed by the users. The task of the workshop consists in the design of the automatic control system that commands the approvision pump of the water tower.

Four reduced scale laboratory water towers have been build and foreseen with the same sensors and actuators as the real water towers [Figure 47].

These sensors and actuators are connected to a computer (a PC) which is in charge of the control.

No deep theory about control is requested in this workshop, only common sense is needed to write a good working control algorithm.

The students are grouped in entities of 6 to 7 working on the same project.

All groups have to reach the same goal, but have to choose their equipment:

- which type of sensor or actuator
- which type of electronic interface
- which type of PC and software

Each group can spend a fictitious credit of 10 k€ to buy the chosen equipment.

The evaluation of each group is based on the obtained technical performances during a test run and on the amount of credit used.

3.4.2 Aim of the workshop and pedagogy.

The aim of the workshop is to show the students a broad overview of the different aspects of electro technics in its ICT taste and initiate them to the first possible and simple applications of basic concepts of mechanics, electricity and chemistry already learned in the semesters 1 to 3.

Also we choose to do it as a project-based learning pedagogy because it opens a lot of human aspects of the engineering job, like the ability to express (oral and written), to work in group, to manage a work plan and to manage a timing.

Figure 47: Scale laboratory water tower
3.5 COURSES LECTURED IN THE FACULTY OF SCIENCE AND BIO-ENGINEERING

<table>
<thead>
<tr>
<th>Lectures and practical courses</th>
<th>Credits</th>
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<tbody>
<tr>
<td>Berekenbaarheid en informatietheorie(^2) - Prof. L. Van Biesen</td>
<td>6</td>
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<tr>
<td><strong>Computability and Information Theory</strong></td>
<td></td>
</tr>
<tr>
<td>1(^{st}) Year Master of Applied Sciences and Engineering: Computer Science (compulsory)</td>
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<tr>
<td>Geographical Information Systems - Prof. L. Van Biesen</td>
<td>3</td>
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<tr>
<td>2(^{nd}) Year Master of Ecological Marine Management (compulsory)</td>
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<tr>
<td>2(^{nd}) Year Master of Applied Sciences and Engineering: Applied Computer Science (optional)</td>
<td></td>
</tr>
<tr>
<td>2(^{nd}) Year Master of Science Ecological Marine Management (compulsory)</td>
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<tr>
<td>Theory of Computation and Information Theory - Prof. L. Van Biesen</td>
<td>6</td>
</tr>
<tr>
<td>1(^{st}) Year Master of Applied Sciences and Engineering: Computer Science (compulsory)</td>
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<tr>
<td>Analyse, WPO(^3): Mattijs Vandewalle, Dr. Veerle Beelaerts, Griet Monteyne, Dr. Kurt Barbé</td>
<td>14</td>
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<tr>
<td>Analysis, Exercises</td>
<td></td>
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<tr>
<td>1(^{st}) Year Bachelor of Science in Math</td>
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<tr>
<td>Complexe Analyse, WPO(^4): Lieve Lauwers, Dr. Kurt Barbé</td>
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<tr>
<td>Complex Analysis, Exercises,</td>
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<tr>
<td>2(^{nd}) Year Bachelor of Science in Math</td>
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<tr>
<td>Wiskundige statistiek, WPO(^5), Dr. Kurt Barbé</td>
<td>6</td>
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<tr>
<td>Mathematical statistics</td>
<td></td>
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<tr>
<td>3(^{rd}) Year Bachelor of Science in Math</td>
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</tbody>
</table>

3.6 NATIONAL AND INTERNATIONAL COURSES

3.6.1 National courses (since 2003):

**3.6.1.1 Identificatie van systemen (Identification of Systems)**

**Organised by:** University of Gent, “Instituut voor permanente vorming”

**Location:** IVPV - UGent, Technologiepark, 9052 Gent-Zwijnaarde

**Lectured by:** Johan Schoukens and Yves Rolain

**Dates:** 7, 14 and 21 December 2004

Meten en modelleren is een basisactiviteit van vele ingenieurs: modellen worden gebruikt tijdens het ontwerp, in simulatoren en in eindproducten. Het modelleringsproces is een complexe activiteit die in 4 grote delen kan worden opgesplitst: verzamelen van de experimentele data; opstellen van een model; in overeenstemming brengen van een model en data; validatie van de resultaten. Systeemidentificatie biedt een systematische, optimale oplossing en wordt in deze module bestudeerd, met als toepassing de identificeren van dynamische systemen. Hierbij wordt de klemtoon gelegd op het aanbrengen van de ideeën, ondersteund door uitgewerkte Matlab illustraties.

\(^2\) The language of tuition of this course is Dutch

\(^3\) The language of tuition of this course is Dutch

\(^4\) The language of tuition of this course is Dutch

\(^5\) The language of tuition of this course is Dutch
De behandelde topics zijn

- Systeemidentificatie: wat? waarom?
  Een verhelderend voorbeeld
  Goede schatters/slechte schatters, wat mag je ervan verwachten?

- Niet-parametrische identificatie van frequentieresponse functies
  Basisidee: van tijdsignaal tot frequentierespons (FRF)
  Experiment design: keuze van de excitatiesignalen, ruisgevoeligheid, uitmiddelen
  Nietlineaire distorties: detectie, kwalificatie en quantificatie

- Parametrische identificatie van de transferfunctie
  Basisidee: van data tot model
  Tijdsdomein- en frequentiedomein-identificatie

- Identificatie van tijdsvariërende systemen
  Basisidee
  Balans volgsnelheid/ruisgevoeligheid

3.6.1.2 Courses lectured at the Katholieke Universiteit Leuven (KUL)

- Rik Pintelon: "Identificeren van lineaire dynamische systemen" 18 HOC, 36 WPO (4 credits): keuze o.o. in de Master in de wiskundige ingenieurstechnieken
- Johan Schoukens: "Systeemidentificatie en modellering" (6 credits):
  o Master in de ingenieurswetenschappen: wiskundige ingenieurstechnieken
  o Master in de ingenieurswetenschappen: bouwkunde
  o Master in de wiskunde
  o Master in de ingenieurswetenschappen: wiskundige ingenieurstechnieken, programma voor industrieel ingenieurs of master industriële wetenschappen (aanverwante richting) (na toelating)
- Yves Rolain: "Metten en modelleren" keuze o.o. in de Master in de wiskundige ingenieurstechnieken

3.6.2 International courses (since 2003):

3.6.2.1 Characterisation of Multiport Systems through 3-port LSNA Measurements
Location: Seminar at NIST, Boulder, CO, December 2003
Lectured by: Wendy Van Moer
# attendees: 20

3.6.2.2 The use of multisines
Location: Seminar at NIST, Boulder, CO, December 2003
Lectured by: Daan Rabijns
# attendees: 20

3.6.2.3 GIS training in SEAFDEC, Thailand
Location: Samut Prakan SEAFDEC/Training Department, Thailand, Bangkok, 2005
Lectured by: Tesfazghi Ghebre Egziabeher

The theme of the course was interrelated to the use of Geographic Information System for Fishery Management. Participants of the course were members of the Southeast Asian Fisheries
Development and Training Center (SEAFDC/TD), who were professionally engaged in the fishing industry.

3.6.2.4  **Measuring, Modeling, and Designing in a Nonlinear Environment**

**Location:** tutorial workshop organized at I2MTC08, Vancouver, Canada, May 2008

**Lectured by:** Yves Rolain, Ludwig De Locht, Rik Pintelon, Johan Schoukens, Wendy Van Moer

**Topics:**

- Best linear approximation and design: A perfect marriage (L. De Locht)
- Measurement of the Best Linear Approximation of Nonlinear Systems (W. Van Moer)
- Impact of nonlinear distortions on the linear framework (J. Schoukens)
- Frequency Response Function Measurement in the Presence of Nonlinear Distortions (R. Pintelon)

3.6.2.5  **VUB - doctoral school on Identification of Nonlinear Dynamic Systems**

**Location:** Dept. ELEC, Vrije Universiteit Brussel, Building K, 6th floor

**Lectured by:** Ludwig De Locht, Rik Pintelon, Johan Schoukens, Gerd Vandersteen, Wendy Van Moer

**# attendees:** 18 (8 different nationalities) in 2008 and 14 (9 different nationalities) in 2010

The department ELEC of the VUB, organized a 4 weeks doctoral school (from the 26th of May till the 20th of June in 2008, from 16th May till the 21st of June in 2009 and from the 6th of June till the 2nd of July in 2010) to give an intensive training on advanced modelling and simulation techniques of (non)linear dynamic systems, starting from experimental data. Half of the time has been spent on courses/exercises, the other half on a project to get hands-on experience. The material taught during the courses and exercises has been put into practice during a clearly defined project, in order to get hands-on experience. The course covered the following topics:

- A basic introduction to system identification,
- Identification of dynamic systems,
- Measuring and modelling of nonlinear systems,
- Simulation tools for nonlinear systems,
- Design and characterization of high-frequency (nonlinear) systems (optional: intended for those with an interest in microwave systems).

The next doctoral school on Identification of Nonlinear Dynamic Systems will be organised in June 2011 (from the 9th of May 2011 till the 3rd of June 2011). Participation to this workshop offers a number of advantages. Besides the training, it can also be the start of a collaboration. To some of the participants we can offer a one year grants to start a research collaboration, or even a full four years grant for a (joint) PhD.

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Interested candidates are invited to send their curriculum vitae, together with a short motivation why they would like to follow this course, and this before the 17th of February 2011. They can also express their interest in the possibility for a longer cooperation. Please do not hesitate to contact us if you would like to have more information: email: dolivaur@vub.ac.be or johan.schoukens@vub.ac.be.
4. Bibliography

4.1 BOOKS

b1. Identification of Linear Systems: A Practical Guideline to Accurate Modeling
J. Schoukens, R. Pintelon
The book is concentrated on the problem of accurate modelling of linear time invariant systems. These models can be continuous time (Laplace-domain) or discrete time (Z-domain). The complete experimental procedure is discussed: how to create optimal experiments (optimization of excitation signals), how to estimate the model parameters from the measurements, how to select between different models, etc. These problems are thoroughly discussed in the first section of the book. A profound theoretical development of the proposed identification algorithm is also made in this section. The second part consists of detailed illustrations of the proposed algorithms on practical problems: modelling an electronic, electrical, acoustic, mechanical system. Finally the book is completed with a practical guideline to help the user making the correct choices.
The book is intended for all those dealing with "practical" modelling problems and have to combine measurements and theory. A second group of interested people are those involved with identification theory.

b2. System Identification: A Frequency Domain Approach
Rik Pintelon, Johan Schoukens
How does one model a linear dynamic system from noisy data? This book presents a general approach to this problem, with both practical examples and theoretical discussions that give the reader a sound understanding of the subject and of the pitfalls that might occur on the road from raw data to validated model. The emphasis is on robust methods that can be used with a minimum of user interaction.
System Identification: A Frequency Domain Approach is written for practising engineers and scientists who do not want to delve into mathematical details of proofs. Also, it is written for researchers who wish to learn more about the theoretical aspects of the proofs. Several of the introductory chapters are suitable for undergraduates. Each chapter begins with an abstract and ends with exercises, and examples are given throughout.

4.2 CHAPTER IN BOOK (2010)

ch1. Blind Maximum-likelihood Identification of Wiener and Hammerstein Nonlinear Block Structures
Laurent Vanbeeylen and Rik Pintelon
In this chapter, we present results on the identification of some simple nonlinear block-oriented systems from output measurements only (blind identification) in the discrete-time setting. We deal with Wiener and Hammerstein models, which consist of a dynamic linear block, respectively followed or preceded by a static nonlinear block. A Gaussian maximum-likelihood estimator is constructed assuming that the unobserved input is white Gaussian noise, that the linear block is minimum-phase, that the static nonlinearity is invertible, and that the output measurements are noise-free. In practice, the (output) data processing procedure starts with the generation of high quality initial estimates. Next, a Gauss-Newton iterative scheme is used to minimize the derived maximum-likelihood cost function, and asymptotic uncertainty bounds are computed. Finally, the bias error introduced by additive output noise is discussed. The theoretical results are illustrated with simulation examples and laboratory measurements.

ch2. Identification of Wiener-Hammerstein Systems Using the Best Linear Approximation
Lieve Lauwers and Johan Schoukens

More publications of the department ELEC can be found on:
or http://wwwtw.vub.ac.be/elec/Papers%20on%20web/index.html
Nonlinear block-oriented models have successfully been used in many engineering applications to identify chemical, mechanical, and biological systems or processes. Due to their simple structure, these models are very attractive from a user’s point of view. However, the block-oriented approach also has some disadvantages over black-box modelling approaches.

4.3 JOURNAL PAPERS (2010)

p351. Continuous-time operational modal analysis in the presence of harmonic disturbances—The multivariate case
R. Pintelon, B. Peeters, P. Guillaume

p352. Fingerprinting Localization in Wireless Networks Based on Received-Signal-Strength Measurements: A Case Study in WiMAX Networks
Mussa Bshara, Umut Orguner, Fredrik Gustafsson, Leo Van Biesen
IEEE Transactions on Vehicular Technology, Vol. 59, No. 1, January 2010
This paper considers the problem of fingerprinting localization in wireless networks based on received-signal-strength (RSS) observations. First, the performance of static localization using power maps (PMs) is improved with a new approach called the base-station-strict (BS-strict) methodology, which emphasizes the effect of BS identities in the classical fingerprinting. Second, dynamic motion models with and without road network information are used to further improve the accuracy via particle filters. The likelihood-calculation mechanism proposed for the particle filters is interpreted as a soft version (called BS-soft) of the BS-strict approach applied in the static case. The results of the proposed approaches are illustrated and compared with an example whose data were collected from a WiMAX network in a challenging urban area in the capital city of Brussels, Belgium.

p353. Odd random phase multisine EIS as a detection method for the onset of corrosion of coated steel
Tom Breugelmans, Els Tourwé, Yves Van Ingelgem, Jan Wielant, Tom Hauffman, René Hausbrand, Rik Pintelon, Annick Hubin
Electrochemistry Communications 12 (2010) 2–5
In this work, odd random phase multisine Electrochemical Impedance Spectroscopy (ORP-EIS) was used as a detection method for the onset of corrosion of coated steel. The possibility to use ORP-EIS as a rapid-screening test for corrosion was investigated. It is concluded that the detection of a non-linear behavior combined with a non-stationary behavior during the onset of corrosion can be used as a criterion in a rapid-screening test for corrosion of coated steel.

p354. Measuring the out-of-band best linear approximation
Wendy Van Moer and Yves Rolain
Measurement & Science Technology, Vol. 21, No. 1, January 2010 (6pp)
A very easy and quick approach to gain insight into the linear as well as the nonlinear behavior of a device under test is the best linear approximation (BLA). The BLA is a linearized model of a nonlinear system and consists of a linearized transfer function combined with a noise source that describes the stochastic nonlinear contributions. Recently, the theory of the BLA has been extended to the out-of-band BLA. This paper describes a measurement technique to determine the out-of-band BLA for microwave systems. The theory is proven on amplifier measurements.

p355. NVNA Versus LSNA: Enemies or Friends?
Wendy Van Moer and Liesbeth Gommé
IEEE Microwave Magazine, February 2010, pp. 97-103
Nonlinearities are becoming very hot! After some years of hesitation, the high-frequency measurement world finally has acknowledged the need to measure the nonlinear behavior of a device or system correctly. Pushed by the modeling world, which clearly needs good nonlinear measurements to obtain good nonlinear models, some “nonlinear” measurement instruments were developed. Two different approaches to design a measurement instrument that is able to measure the nonlinear time domain waveforms correctly can be followed: a sampler-based methodology or a mixer-based methodology.

Kurt Barbé, Rik Pintelon, and Johan Schoukens
The objective of this paper is twofold. The first part provides further insight in the statistical properties of the Welch power spectrum estimator. A major drawback of the Welch method reported in the literature is that the variance is not a monotonic decreasing function of the fraction of overlap. Selecting the optimal fraction of overlap, which minimizes the variance, is in general difficult since it depends on the window used. We show that the explanation for the nonmonotonic behavior of the variance, as reported in the literature, does not hold. In the second part, this extra insight allows one to eliminate the nonmonotonic behavior of the Welch power spectrum estimator (PSE) by introducing a small modification to the Welch method. The main contributions of this paper are providing extra insight in the statistical properties of the Welch PSE; modifying the Welch PSE to circular overlap—the variance is a monotonically decreasing function of the fraction of overlap, making the method more user friendly; and an extra reduction of variance with respect to the Welch PSE without introducing systematic errors—this reduction in variance is significant for a small number of data records only.

p357. Accuracy analysis of time domain maximum likelihood method and sample maximum likelihood method for errors-in-variables and output error identification
Torsten Söderström, Mei Hong, Johan Schoukens, Rik Pintelon
For identifying errors-in-variables models, the time domain maximum likelihood (TML) method and the sample maximum likelihood (SML) method are two approaches. Both methods give optimal estimation accuracy but under different assumptions. In the TML method, an important assumption is that the noise-free input signal is modelled as a stationary process with rational spectrum. For SML, the noise-free input needs to be periodic. It is interesting to know which of these assumptions contain more information to boost the estimation performance. In this paper, the estimation accuracy of the two methods is analyzed statistically for both errors-in-variables (EIV) and output error models (OEM). Numerical comparisons between these two estimates are also done under different signal-to-noise ratios (SNRs). The results suggest that TML and SML have similar estimation accuracy at moderate or high SNR for EIV. For OEM identification, these two methods have the same accuracy at any SNR.

p358. Identification of nonlinear systems using Polynomial Nonlinear State Space models
Johan Paduart, Lieve Lauwers, Jan Swevers, Kris Smolders, Johan Schoukens, Rik Pintelon
In this paper, we propose a method to model nonlinear systems using polynomial nonlinear state space equations. Obtaining good initial estimates is a major problem in nonlinear modeling. It is solved here by identifying first the best linear approximation of the system under test. The proposed identification procedure is successfully applied to measurements of two physical systems.

p359. Modeling the Series Impedance of a Quad Cable for Common-Mode DSL Applications
Wim Foubert, Carine Neus, Leo Van Biesen, and Yves Rolain
"New digital subscriber line (DSL) technologies are being developed to meet the ever-increasing bandwidth demand of the user. One very promising approach injects "common-mode" signals that superimpose a signal on two regular differential pairs. This technique requires new reliable multiconductor models for the telephony cables. Therefore, good approximations of the series impedance of the line are indispensable. In this paper, a model for this series impedance is theoretically derived and validated with measurements."

p360. Phase separation in polymer blend thin films studied by differential AC chip calorimetry
Nicolaas-Alexander Gotzen, Heiko Huth, Christoph Schick, Guy Van Assche, Carine Neus, Bruno Van Mele
AC chip calorimetry is used to study the phase separation behavior of 100 nm thin poly(vinyl methyl ether)/poly(styrene) (PVME/PS) blend films. Using the on-chip heaters, very short (10 MS-10 S) temperature jumps into the temperature window of phase separation are applied, simulating laser heating induced patterning. These temperature pulses produce a measurable shift in the glass transition temperature, evidencing phase separation. The effect of pulse length and height on phase separation can be studied. The thus phase separated PVME/PS thin films remodel rapidly, in contrast with measurements in bulk. AC chip calorimetry seems to be a more sensitive technique than atomic force microscopy to detect the early stages of phase separation in polymer blend thin films.

p361. Estimation of nonparametric noise and FRF models for multivariable systems—Part I: Theory
R. Pintelon, J. Schoukens, G. Vandersteen, K. Barbé
This series of two papers presents a method for estimating nonparametric noise and frequency response function models of multivariable linear dynamic systems excited by arbitrary inputs. It extends the results of Schoukens et al. (2006) [1] and Schoukens and Pintelon (2009) [2] from single input, single output systems with known input and noisy output observations (output error problem), to multiple input, multiple output systems where both the input and output are disturbed by noise (errors-in-variables problem). In Part I, the theory is developed for linear dynamic multivariable output error problems. The results are supported by simulations. A detailed comparison with the classical spectral analysis based on correlation techniques shows that the proposed procedures are more robust.
In Part II (Pintelon et al., 2009) [3], the method first is applied to nonlinear systems, and parametric identification within a generalized output error framework. Next, it is extended to handle errors-in-variables problems, and identification in feedback. Finally, it is illustrated on four real measurement examples.

**p362. Estimation of nonparametric noise and FRF models for multivariable systems—Part II: Extensions, applications**

R. Pintelon, J. Schoukens, G. Vandersteen, K. Barbé

This is Part II of a series of two papers on the estimation of nonparametric noise and frequency response function models for multiple input, multiple output systems excited by arbitrary inputs. Part I (Pintelon et al. (2009)) [1] develops the methodology for linear dynamic multivariable systems with exactly known input and where the output is disturbed by stationary noise (=output error problem). The contributions of Part II are the following. First, it is shown that the proposed method can be used for nonlinear systems and for parametric identification of the system dynamics in a generalized output error framework. Next, the methodology is generalized to handle noisy input-output data (= errors-in-variables problem), and identification in feedback. Finally, the approach is illustrated on simulations and real measurements examples.

**p363. Estimation of the equivalent complex modulus of laminated glass beams and its application to sound transmission loss prediction**

K. De Belder, R. Pintelon, C. Demol, P. Roose

The complex modulus $E(j\omega)$ characterizes the visco-elastic behavior of a material. Using a system identification approach, this modulus can be measured via broadband modal analysis experiments. The technique is applied to determine the equivalent complex modulus $E(j\omega)$, with its uncertainty bound, of multilayer glass beams from transversal vibration experiments in free-free boundary conditions. This property is related to the effective complex bending stiffness of the laminated glass specimen, and is further used for predicting the sound transmission loss of a multilayer plate. The data are rationalized in the terms of the linear visco-elastic properties of the polymer interlayer.

**p364. An Armax Identification Method for Sigma-Delta Modulators Using Only Input-Output Data**

G. Vandersteen, M. Jain and R. Pintelon

“Sigma-delta modulators are becoming increasingly more popular in electronic circuits. They are characterized via their signal and noise transfer functions (STF and NTF). This linearized model is basically an autoregressive moving average model with exogenous inputs (ARMAX model), which is used during the design of the modulator. Hence, the pole/zero locations of its transfer functions give valuable information about the system. The identification of the poles and zeros from input/output data enables the verification of the complete $\Delta \Sigma$ modulator and can be used on actual measurements where the internal signals are not accessible. The identification of ARMAX models from input-output data is well studied in the literature under conditions that are generally met in control applications. However, $\Delta \Sigma$ modulators are designed such that these general assumptions are violated. This paper gives an overview of the properties of $\Delta \Sigma$ modulators and compares the pros and cons of both time- and frequency-domain identification techniques for ARMAX systems. Then, it discusses a modified frequency-domain approach to identify the $\Delta \Sigma$ modulator starting from its input-output data. The technique is illustrated on both low-pass and bandpass $\Delta \Sigma$ modulators, showing an excellent agreement between the theoretical and estimated transfer functions.”

**p365. Upper Bounding Variations of Best Linear Approximations of Nonlinear Systems in Power Sweep Measurements**

J. Schoukens, T. Dobrowiecki, Y. Rolain, R. Pintelon

In many engineering applications, linear models are preferred, even if it is known that the system is nonlinear. A large class of nonlinear systems, excited with random excitations, can be represented as $Y = GLBAU + YS$ with GLBA the best linear approximation, and $YS$ a nonlinear noise source that represents that part of the output that is not captured by the linear approximation. Because GLBA not only depends upon the linear dynamics, but also on the nonlinear distortions, it will vary if the input power is changed. In this paper, we study under what conditions (class of excitations, class of nonlinear systems) these variations of GLBA can be bounded, starting from the knowledge of the power spectrum SYs. Since SYs can be easily measured using well designed measurement procedures, it becomes possible to provide the designer with an upper bound for the variations of GLBA, leading to more robust design procedures.

**p366. Multirate Cascaded Discrete-Time Lowpass Delta Sigma Modulator for GSM/Bluetooth/UMTS**

Lynn Bos, Gerd Vandersteen, Pieter Rombouts, Arnd Geis, Alonso Morgado, Yves Rolain, Geert Van der Plas and Julien Ryckaert
This paper shows that multirate processing in a cascaded discrete-time 16 modulator allows to reduce the power consumption by up to 35%. Multirate processing is possible in a discrete-time 16 modulator by its adaptability with the sampling frequency. The power reduction can be achieved by relaxing the sampling speed of the first stage and increasing it appropriately in the second stage. Furthermore, a cascaded 16 modulator enables the power efficient implementation of multiple communication standards. The advantages of multirate cascaded 16 modulators are demonstrated by comparing the performance of single-rate and multirate implementations using behavioral-level and circuit-level simulations. This analysis has been further validated with the design of a multirate cascaded triple-mode discrete-time 16 modulator. A 2-1 multirate low-pass cascade, with a sa

p367. Identification and quantification of nonlinear stiffness and nonlinear damping in resonant circuits
M.L.D. Lumori, J. Schoukens, J. Lataire
This paper presents a study of nonlinear vibrating mechanical structures whose resonances have nonlinearities due to stiffness and/or damping. A method is presented to detect the presence of nonlinear distortions qualitatively and quantitatively. Basically, a device under test is configured as a second-order, single-input–single-output closed-loop feedback system where static nonlinearities are confined to the feedback path, and the dynamic linear part is modeled as the forward gain. The system is excited by a random phase multisine, which allows for the modeling of the linear part by its frequency response function, thus facilitating the characterization of the nonlinear part. The identification is formulated in a linear-in-parameters framework, using input and output regressors. Good agreement on the estimation of the nonlinearities due to stiffness and damping with distinguishable levels.

p368. Time-Series Reconstruction from Natural Archive Data with the Averaging Effect
Veerle Beelaerts, Fjo De Ridder, Nele Schmitz, Maite Bauwens, Rik Pintelon
Environmental information of the past can be obtained by processing and analyzing proxies recorded by environmental archives. Natural archives are sampled at a distance grid along their accretion axis. Starting from these distance series, a time series needs to be constructed, because comparison of different data records is only meaningful on a time grid. However, distance-time relationships are nonlinear as the accretion rate of natural archives is dependent on environmental and physiological factors. Furthermore, in environmental archives, samples are taken over a volume in distance, rather than over a point in distance. This implies that the sample-values will be averaged over the volume of the sample. In this paper a method is proposed, which establishes the nonlinear distance-time relationship and corrects for the averaging effects. The method is built upon the assumption that the proxy record on a time axis is harmonic. If this is not the case, then a harmonic approximation is made. As a consequence of the nonlinear distance-time relationship, this harmonic proxy signal is nonlinearly distorted on a distance axis. As such, a harmonic signal model with a nonlinear phase distortion and an averaging effect is fitted on the data. Since environmental records are short data records, the statistical performance of the estimator on noisy data is verified by means of Monte Carlo simulations. The applicability of the method is demonstrated on the measurement of the vessel density, in a mangrove tree, Rhizophora mucronata, which is an indicator of the rainfall in tropical coastal ecosystems.

p369. Fast detection of system nonlinearity using nonstationary signals
E. Zhang, J. Antoni, R. Pintelon, J. Schoukens
This paper proposes a method for the detection and quantification of nonlinear distortions in the output of a dynamic system. The basic idea is to use a nonstationary excitation that makes the nonlinear distortions also nonstationary, thus making possible their differentiation from stationary plant noise. The nonstationarity of the excitation allows the evolution of the system nonlinearity to be assessed in one single shot, thus greatly accelerating the experiment.

p370. A nonlinear multi-proxy model based on manifold learning to reconstruct water temperature from high resolution trace element profiles in biogenic carbonates
M. Bauwens, H. Ohlsson, K. Barbé, V. Beelaerts, F. Dehairs, and J. Schoukens
Geoscientific Model Development Discussions, 3, pp. 1105–1138, 2010
A long-standing problem in paleoceanography concerns the reconstruction of water temperature from 180 carbonate, which for freshwater influenced environments is hindered because the isotopic composition of the ambient water (related to salinity) affects the reconstructed temperature. In this paper, we argue for the use of a nonlinear multi-proxy model called Weight Determination by Manifold Regularization to develop a temperature reconstruction model that is less sensitive to salinity variations. The motivation for using this type of model is twofold: Firstly, observed nonlinear relations between specific proxies and water temperature motivate the use of nonlinear models. Secondly, the weight of multi-proxy models enables salinity-related variations of a given temperature proxy to be explained by salinity-related information carried by a separate proxy. Our studies confirm that Mg/Ca is a powerful paleothermometer and highlight that reconstruction performance based on this proxy is improved significantly by combining its information with the information of other trace elements in multi-proxy 15 models. Using Mg/Ca, Sr/Ca, Ba/Ca and Pb/Ca the WDMR model enabled a temperature reconstruction with a root mean squared error of ±2.19 C for a salinity range between 15 and 32.

p371. Nonlinear Induced Variance of Frequency Response Function Measurements
Johan Schoukens, Kurt Barbé, Laurent Vanbeylen and Rik Pintelon
Annual report ELEC 2010

This paper analyzes the variance of the estimated frequency response function (FRF) \( \hat{G}_{BLA} \) of the best linear approximation GBLA to a nonlinear system that is driven by random excitations. \( \hat{G}_{BLA} \) varies not only due to the disturbing measurement and process noise but also over different realizations of the random excitation because the nonlinear distortions depend on the input realization. It will be shown that the variance expression \( \sigma^2 \) \( G_{BLA} \) that is obtained in the linear framework can also be used to calculate the variance that is induced by the nonlinear distortions. This validates the common engineering practice, where the linear FRF methodology is often used under nonlinear conditions.

### Two Nonlinear Optimization Methods for Black Box Identification Compared Reference

Anne Van Mulders, Johan Schoukens, Marnix Volckaert, Moritz Diehl

Automatica, Volume 46, Issue 10, October 2010, Pages 1675-1681

In this paper, two nonlinear optimization methods for the identification of nonlinear systems are compared. Both methods estimate the parameters of e.g. a polynomial nonlinear state-space model by means of a nonlinear least-squares optimization of the same cost function. While the first method does not estimate the states explicitly, the second method estimates both states and parameters adding an extra constraint equation. Both methods are introduced and their similarities and differences are discussed utilizing simulation data. The unconstrained method appears to be faster and more memory efficient, but the constrained method has a significant advantage as well: It is robust for unstable systems of which bounded input–output data can be measured (e.g. a system captured in a stabilizing feedback loop). Both methods have successfully been applied on real-life measurement data.

### Oscillometric Blood Pressure Measurements: a signal analysis

Kurt Barbé, Wendy Van Moer and Lieve Lauwers


In this paper, the oscillometric waveform measured by automatic non-invasive blood pressure meters (NIBP) is analyzed by transforming the data from the time domain to the frequency domain. The signal's spectrum of the oscillometric waveform is in current literature badly understood or explored. The only known link between the oscillometric waveform and the blood pressure is the maximum of the osccilometry's envelope equaling the mean arterial pressure (MAP). This link is established under the assumption that the oscilometry is an AM-signal. Unfortunately, computing the MAP is difficult in practice due to the non-sinusoidal nature of the actual measured signals. In this paper, we construct the best AM-signal approximation of the osccilometry and explore its use to compute the MAP.

### Analyzing Rice distributed functional MRI data: a Bayesian approach

Lieve Lauwers, Kurt Barbé, Wendy Van Moer and Rik Pintelon


Analyzing functional MRI data is often a hard task due to the fact that these periodic signals are strongly disturbed with noise. In many cases, the signals are buried under the noise and not visible, such that detection is quite impossible. However, it is well known that the amplitude measurements of such disturbed signals follow a Rice distribution which is characterized by two parameters. In this paper, an alternative Bayesian approach is proposed to tackle this two-parameter estimation problem. By incorporating prior knowledge into a mathematical framework, the drawbacks of the existing methods (i.e. the maximum likelihood approach and the method of moments) can be overcome. The performance of the proposed Bayesian estimator is analyzed theoretically and illustrated through simulations. Finally, the developed approach is successfully applied to measurement data for the analysis of functional MRI.

### A 0.5mm2 power scalable 0.5-3.8 GHz CMOS DT-SDR receiver with 2nd order RF band-pass sampler

A. Geis, J. Ryckaert, L. Bos, G. Vandersteen, Y. Rolain, J. Craninckx


A highly flexible receiver chain based on RF-sampling and discrete-time signal processing in the charge domain for SDR applications is presented. A compact switched-inductor variable-gain front-end provides multiband low noise amplification and RF-selectivity with reduced area penalties. Strong selectivity at RF was obtained through a novel discrete-time decimating bandpass filter with triangular weighted filter taps. Decimation filters with programmable number of taps offer flexible rate decimation. A power scalable discrete-time baseband filter was implemented in-order to minimize static power consumption. The 90-nm digital CMOS implementation achieves a noise figure of 5.1 dB, a variable gain range of more than 60 dB with approx. 1 dBm IIP3 and

### Nonlinear least-squares modeling of 3D interaction position in a monolithic scintillator block

Zhi Li, M Wedrowski, P Bruyndonckx and G Vandersteen

Physics in Medicine and Biology, Vol. 55, No. 21, pp. 6515-6532

This paper presents a study of possible models to describe the relation between the scintillation light point-of-origin and the measured photo detector pixel signals in monolithic scintillation crystals. From these models theoretical and depth of interaction (DOI) coordinates can be estimated simultaneously by nonlinear least-square fitting. The method depends only on the information embedded in the signals of individual events, and therefore does not need any prior position training or calibration. Three possible distributions of the light sources were evaluated: an exact solid-angle-based distribution, an approximate solid-angle distribution and an extended approximate solid-angle-based distribution which includes internal reflection at side and bottom surfaces. The performance of the general model
4.4 CONFERENCE PAPERS (2010)

c755. Identification of Stiffness and Damping in Nonlinear Systems
Mikay LD Lumori, Johan Schoukens, John Lataire
Proceedings of the IMAC-XXVIII, February 1-4, 2010, Jacksonville, Florida USA
"Resonance nonlinearities in vibrating mechanical structures are either due to stiffness, damping, or a combination of both. A method is presented to detect the nonlinear distortions, determine and quantify the distortion levels. This is achieved by configuring a nonlinear device as a second-order, single-input-single-output (SISO) closed-loop feedback system such that static nonlinearities are confined to the feedback path, and the dynamic linear part is modeled as the forward gain. The closed-loop system is then subjected to random phase multisinew excitations. This makes it possible to model the linear part by its frequency response function, thus facilitating the characterization of the nonlinear part. There is a good agreement between the estimated and experimental data. The results indicate distortion nonlinearities due to stiffness and damping with distinguishable levels."

c756. Assigning the Nonlinear Distortions of a Two-input Single-output System
W. D. Widanage, J. Schoukens
Proceedings of the IMAC-XXVIII, February 1-4, 2010, Jacksonville, Florida USA
In a multiple-input multiple-output (MIMO) nonlinear system the nonlinear contributions from each input to each output may vary significantly. The nonlinear distortions are composed of contributions that are either purely due to each individual input or a combination with some of the inputs. A three stage experimental design method valid for a wide range of nonlinear systems is presented that detects and classifies, in the frequency domain, the level of these combinations is conditioned by the operating levels. Periodic broadband excitation signals with several harmonics suppressed are used as the inputs to reduce the noise contributions and evaluate the nonlinear distortion levels present at the suppressed harmonics. Alternatively, each input signal can be designed with a harmonic specification such that the harmonics of the output signal indicate the presence of these nonlinear contributions. As a single experiment technique it requires less time for measurements, however the input harmonics become very sparse as the order of the nonlinearity increase that the signals become impractical for experimental use. Experimental results for a two-input single-output system are presented demonstrating the effectiveness of the techniques.

c757. Frequency Domain Tracking of Time-Varying Modes
John Lataire, Rik Pintelon
Proceedings of the IMAC-XXVIII, February 1-4, 2010, Jacksonville, Florida USA
"Many engineering applications involve systems whose dynamics vary with time. Consider, for example, the dynamics of the wings of a plane that is airborne. The resonance modes of the wings, and the associated damping and stiffness are functions of the flight speed and height. Therefore, the dynamics vary as the plane accelerates and/or its altitude increases. This paper provides a methodology for tracking the evolving dynamics of linear, slowly time-varying systems. The responses of the systems to multisinew excitations are explained and shown to provide an insight into the timevarying behavior of the system. The acquired knowledge of the responses is used to estimate non-parametrically the instantaneous frequency response function from one single experiment. A simplified case, where the variations are linear with time, is discussed in this paper. A glance of a generalization procedure to a polynomial variation is given. Results are illustrated on simulations of a lumped time-varying system."

c758. A 0.5mm2 power scalable 0.5-3.8GHz CMOS DT-SDR receiver with 2nd order RF band-pass sampler
Ard Geis, Julien Ryckaert, Gerd Vandersteen, Yves Rolain
We present a highly flexible receiver chain based on RF-sampling and discrete-time signal processing in the charge domain for SDR applications. A switched inductor variable gain front-end provides multi-band low noise amplification and RF-selectivity with reduced area penalties. Strong selectivity at RF was obtained through a novel second order decimating bandpass filter. Decimation filters with programmable number of taps offer flexible rate decimation. A power scalable discrete-time baseband filter was implemented in order to minimize static power consumption. The 90nm digital CMOS implementation achieves a noise figure of 5.1dB, a variable gain range of more than 60dB with 1dBm IIP3 and +50dBm IIP2. This is achieved for power figures competitive with dedicated solutions. The receiver, frequency synthesizer excluded, occupies only 0.5mm2.

c759. Frequency Domain Based Feed Forward Tuning for Friction Compensation
David Rijlaarsdam, Vincent van Geffen, Pieter W.J.M. Nuij, Johan Schoukens and Maarten Steinbuch
ASPE 2010, Spring Topical Meeting in Cambridge, April 10 to 13, Massachusetts, USA
“In high precision motion control, performance is often limited by the presence of nonlinearities. In this study, the presence of nonlinear influences in a high precision transmission electron microscope stage is investigated using broadband multisine signals. These measurements yield the nature and level of nonlinearities as well as the best linear approximation of the dynamics. By quantitatively measuring the level of nonlinear influences, this method indicates the relevance of improved modeling. Next, the nonlinear influences are modeled explicitly by measuring the higher order sinusoidal input describing functions (HOSIDF) of the system which describe the ‘direct’ response of the system at the input frequency as well as at harmonics of the input frequency. Application of this technique yields a structured way to design Coulomb friction feed forward in the presence of nonlinearities. This procedure linearizes the input-output dynamics by applying feed forward and measuring the HOSIDFs which indicate the remaining nonlinear effects. Application of this technique yields a structured way to design feed forward in the presence of nonlinearities.

**c760. Design of excitation signals for nonparametric measurements on MIMO-systems in the presence of nonlinear distortions**

Johan Schoukens, Rik Pintelon, Gerd Vandersteen, Yves Rolain

In this paper we make nonparametric measurements on a system with two inputs and two outputs, in the presence of nonlinear distortions. Starting from a series of experiments, the frequency response function, the covariance matrix of the output noise, and the covariance matrix of the output nonlinear distortions are estimated as a function of the frequency. It will be shown that, using well designed periodic excitations signals, it is possible to obtain these results with little user interaction, making the method accessible for non-experienced users.

**c761. Compensating out-of-band nonlinear distortions**

Wendy Van Moer, Rik Pintelon

In this paper a method is proposed to compensate for the nonlinear distortions present in the input signal of a DUT which results in a source-pull free level of the output nonlinear distortions. This allows to determine an accurate adjacent co-channel power ratio (ACPR). The proposed measurement technique is based on a vector network analyzer (PNA-X) and uses a broadband multisine excitation. Results obtained from a microwave amplifier are reported.

**c762. Noise Leakage Suppression in FRF Measurements Using Periodic Signals**

Rik Pintelon, Kurt Barbé, Gerd Vandersteen, Johan Schoukens

The steady state response of a system to a periodic input is still corrupted by noise transients. For lightly damped systems these noise transients increase considerably the variance of the measured frequency response function (FRF). This paper presents a method that suppresses the influence of the noise transients (leakage errors) in FRF measurements. The method is based on a local polynomial approximation of the noise leakage errors on the FRF. Compared with the classical approaches, the proposed procedure is more robust and needs less measurement time. The theory is supported by a real measurement example.

**c763. Robust small sample properties for likelihood based confidence regions**

Kurt Barbé, Johan Schoukens

Many measurement applications, in particular for biological, biomedical and biochemical systems, deals with the problem that only short data records are available. This problem implies that many powerful statistical tools are not applicable since these tools are based on asymptotic results. No user-friendly guidelines are available when dealing with such sparse datasets. In contrast to an estimator, one often uses an interval estimate when dealing with small data-records. An interval estimate specifies a range within which the parameter is estimated to lie. Confidence intervals are commonly reported in tables or graphs along with point estimates of the same parameters, to show the reliability of the estimates. In this paper, we study the robustness of asymptotically optimal confidence regions to small/finite sample effects. Our study reveals immediate guidelines to the user when dealing with short records.

**c764. Comparison of nonparametric frequency estimators**

David Slepčiča, Dušan Agrež, Rado Lapuh, Emilia Nunzi, Dario Petri, Tomáš Radil, Johan Schoukens, Miloš Sediček
12MTC 2010, International Instrumentation and Measurement Technology Conference, Austin, Texas, 3-6 May, 2010, pp. 73-76

This paper deals with the performance of several up-to-date nonparametric frequency estimators. The algorithms of frequency estimation are introduced and their bias, standard deviation and consumption time are compared with regard to the most common signal parameters.

**c765. An 0.045mm² 0.1-6GHz reconfigurable multi-band, multi-gain LNA for SDR**

A. Geis, Y. Rolain, G. Vandersteen
A low area fully reconfigurable multi-band LNA array based on active feedback amplifiers with mixed resistive and switched inductor loads is presented. The 90nm baseline digital CMOS implementation covers the entire frequency range of interest for SDR from 0.1 to 6GHz with a dynamic gain range from 0dB to 22dB. A noise figure as low as 2.7dB and an input-referred linearity IIP3 of -4dBm at 16dB gain is achieved. An IIP3 of +9dBm is reached in low gain mode to allow for high signal and interferer power at the antenna input. The LNA draws between 10 and 26mA from a 1.2V supply. The active area of the array is only 0.045mm².

A VNA based broadband loadpull for non-parametric 2-port Best Linear Approximation Modelling
Y. Rolain, J. Schoukens, R. Pintelon, L. De Locht, G. Vandersteen
Proceedings of the 75th ARFTG Microwave Measurement Conference, Boston, Massachusetts (USA), May 23-28, 2010, pp. 34-38

In this paper the Best Linear Approximation (BLA) of a full 2-port nonlinear dynamic system is extracted under broadband load-pull conditions. Starting from a series of VNA Measurements and broadband multisine excitations at both ports, the frequency response function, the covariance matrix of the output noise, and the covariance matrix of the output nonlinear distortions are estimated as a function of the frequency. Using well designed periodic excitations, these results are obtained with limited user interaction, making the method accessible for practitioner engineers.

Nonlinear distortion analysis of circuits and systems
Gerd Vandersteen, Ludwig De Locht, Piet Wambaq
presentation of tutorial at ISCAS 2010, May 30th-June 2nd 2010 Paris, France

This tutorial aims to demystify the nonlinear distortion analysis of circuits and systems. Combining the capabilities of analyzing large circuits through simulation-based methods, and the analytical insight provided by symbolic methods, enables the analysis of the nonlinear behavior of complex systems. The simulation-based methods make it possible to pinpoint the dominant nonlinearities, while the symbolic method can be used afterwards to get analytical insight into the nonlinear behavior. Both methods will be demonstrated using a large set of practical examples.

The tutorial first introduces the necessary notions on Volterra theory, starting from classical linear system theory. The analytical expressions provided by Volterra theory result in a better understanding of the behavior of the system. The complexity of the resulting expressions, however, limits this technique to simple systems. Second, the tutorial introduces the Best-Linear-Approximation (BLA) paradigm, which represents the nonlinear system as a linear transfer function and an additive nonlinear distortion component. It enables the separation of the various linear and nonlinear contributions and is able to pinpoint the dominant nonlinear distortions in a complex system in a hierarchical way. The main drawback of the simulation-based methods is, however, the reduced analytical insight. Finally, the power of both methods is combined to study a large set of application examples. Starting from a single-transistor circuit, the circuits’ complexity gradually increases over OPAMPs to active filters, receiver front-ends, and sigma-delta modulators. Both the symbolic method and the simulation-based method are used side-by-side to gain insight in the nonlinear distortion properties of the systems. All results are finally cross-checked and compared with results available in the literature. During the course, the simulation data will be distributed to the attendees in MATLAB data format so they can get familiar with proposed techniques using MATLAB or Octave examples.

Calculating the instantaneous impedance value of a non-stationary electrochemical system by means of ORP-EIS
T. Breugelmans, E. Tourné, J. Lataire, R. Pintelon, and A. Hubin

Electrochemical impedance spectroscopy is a widely used and well-accepted technique to study the properties of organic coatings. However, the interpretation of the experimental impedance spectra is not straightforward and is always based on the modelling of experimental results. With the current state-of-the-art, a necessary condition to obtain a satisfactory model is that the system responds linearly to the excitation signal and that it behaves stationary. Nevertheless, it is possible that the system under study changes during the experiment, especially in the case of corrosion reactions. So stationarity is not always guaranteed. To overcome this problem, we developed an integrated methodology to measure, analyze and model electrochemical systems in a correct and reliable way. This methodology is based on the use of an odd random phase multisine excitation signal (ORP-EIS) [1-3]. One of the advantages of ORP-EIS, is that it offers the possibility to detect the noise level and the contribution of non-stationarities at each frequency. However, detection of a non-stationary behavior is not enough. If we want to try to reduce the contribution of the non-stationarities into account when modelling, we should be able to quantify the non-stationary behavior at each frequency. When exciting a time-invariant system with the odd random phase multisine, the signal at the output is supposed to be present only at the excited frequencies. Therefore, for a purely linear system, the energy on the non-excited lines is entirely due to noise. An idea of the frequency-dependent noise level is thus easily extracted from these non-excited lines. In that case, we can easily quantify the non-stationary behavior by comparing the noise at the excited frequencies with the noise at the non-excited frequencies. When a multisine is applied to a linear but nonstationarities into account when modelling, we should be able to quantify the non-stationary behavior at each frequency. However, detection of a non-stationary behavior is not enough. If we want to try to reduce the contribution of the non-stationarities into account when modelling, we should be able to quantify the non-stationary behavior at each frequency.
c769. Identification and quantification of nonlinear stiffness and nonlinear damping in resonant circuits
M.L.D. Lumori, J. Schoukens, J. Lataire
This paper presents a study of nonlinear vibrating mechanical structures whose resonances have nonlinearities due to stiffness and/or damping. A method is presented to detect the presence of nonlinear distortions qualitatively and quantitatively. Basically, a device under test is configured as a second-order, single-input-single-output closed-loop feedback system where static nonlinearities are confined to the feedback path, and the dynamic linear part is modeled as the forward gain. The system is excited by a random phase multisine, which allows for the modeling of the linear part by its frequency response function, thus facilitating the characterization of the nonlinear part. The identification is formulated in a linear-in-parameters framework, using input and output regressors. A good agreement between the estimated data and the measurements indicates the presence of nonlinearities due to stiffness and damping with distinguishable levels.

c770. Frequency Domain Total Least Squares Estimator of Time-Varying Systems
John Lataire, Rik Pintelon
An identification procedure for linear continuous-time, time-varying systems is presented. The model considered is an ordinary differential equation whose coefficients are polynomials in time. The model equation is evaluated in the frequency domain (thus allowing a simple selection of the frequency band of interest) from sampled, finite length records of the input and output signals. The time-frequency transformations are performed using the Discrete Fourier Transform and its inverse. The leakage and alias errors (due to the non-periodicity of the system's response) are shown to be easily captured by adding a polynomial to the model equation. The identification procedure is formulated as a total least squares estimation problem. The estimator is illustrated on a simulation example.

c771. Oscillometric Blood Pressure Measurements: a signal analysis
Kurt Barbé, Wendy Van Moer and Lieve Lauwers
13th IMEKO TC1-TC7 Joint Symposium, "Without Measurement No Science, Without Science No Measurement", 1 - 3 September 2010, City University London
In this paper, the oscillometric waveform measured by automatic non-invasive blood pressure meters (NIBP) is analyzed by transforming the data from the time domain to the frequency domain. The signal's spectrum of the oscillometric waveform is in current literature badly understood or explored. The only known link between the oscillometric waveform and the blood pressure is the maximum of the oscillometry’s envelope equaling the mean arterial pressure (MAP). This link is established under the assumption that the oscilometry is an AM-signal. Unfortunately, computing the MAP is difficult in practice due to the non-sinusoidal nature of the actual measured signals. In this paper, we construct the best AM-signal approximation of the oscilometry and explore its use to compute the MAP.

c772. A simple and fast technique to evaluate the possibility of approximating a nonlinear system by a nonlinear PISPO model
Anna Marconato, Anne Van Mulders, Rik Pintelon, Yves Rolain, Johan Schoukens
UKACC International Conference on CONTROL 2010, Coventry, UK, 7-10 September 2010, pp. 674-679
In this paper we present a simple approach that allows one to decide whether a nonlinear Periodic Input Same Period Output (PISPO) model can be successfully used for nonlinear system identification, in particular when nonperiodicities are present on the output. The proposed technique consists of a nonparametric preprocessing step based on a periodic analysis, combined with the estimation of the parametric best linear approximation.

c773. Semi-parametric identification of parallel Hammerstein systems
Maarten Schoukens, Yves Rolain, Rik Pintelon and Johan Schoukens
UKACC International Conference on CONTROL 2010, Coventry, UK, 7-10 September 2010, pp 937-942
In this paper, a semi-parametric identification method for parallel Hammerstein systems is proposed. The static nonlinearities are represented as a linear combination of basis functions, the linear dynamic systems are represented by their nonparametric frequency response function (FRF). A three step procedure is used. In the first step, the FRF of the best linear approximation is estimated for different excitation levels. In the second step, the varying dynamics are decomposed over a number of parallel branches using a singular value decomposition (SVD). In the last step, the static nonlinearities are estimated using a linear least squares estimation. The method is illustrated on a series of simulations.

c774. High Quality Frequency Response Function Measurements without User Interaction
Johan Schoukens and Rik Pintelon
UKACC International Conference on CONTROL 2010, Coventry, UK, 7-10 September 2010, pp 932-936
In this paper we propose a method to measure the frequency response function (FRF) of a system using arbitrary excitations without any user interaction. The choice of the excitation is left free, arbitrary, random, or periodic
excitations are allowed depending on the preference of the user. The local polynomial method (LPM) is used to reduce the leakage errors on the FRF to extremely low levels compared with what is obtained with the classical windowing methods. The LPM provides also an estimate of the disturbing noise variance as a function of the frequency. The only parameter to be tuned in this method is the local bandwidth that sets how many neighbouring frequency lines are combined in a single point estimate. In this paper we propose a modified AIC-criterion to address this question so that the mean square error of the estimates is minimised.

Nonparametric modelling of a linear time varying system
W. Dhammika Widanage, John Lataire and Johan Schoukens
UKACC International Conference on CONTROL 2010, Coventry, UK, 7-10 September 2010, pp. 1190-1195
The paper studies the frequency response estimation of a time varying system. The system is a sum of two parallel branches, one being a linear time invariant (LTI) branch and the other an LTI followed by a time-varying gain. A method is presented that shows how such a system can be modelled nonparametrically and gives estimates for the frequency response functions when excited by an arbitrary input signal. The frequency response of a linear system and the transient error that arises when using arbitrary signals to model the input-output behaviour are smooth functions of frequency. By a polynomial approximation of the functions and considering the time varying effect, a model that is linear in the parameters is obtained. The method is evaluated on a simulated system showing the level of the modelling error along with the estimated frequency responses, their variances and the variance of any disturbing noise at the output.

A 100kHz-10MHz BW, 78-to-52dB DR, 4.6-to-11mW Flexible SC Sigma-Delta Modulator in 1.2-V 90-nm CMOS
A. Morgado, R. del Rio, J. de la Rosa, L. Bos, J. Ryckaert, and G. Van der Plas
IEEE European Solid-State Circuits Conference (ESSCIRC), 14 - 16 September 2010.
This paper presents an adaptive 1.2-V 90-nm CMOS cascade two-stage (2-2) SC ΣΔ modulator with 3-level quantization and unity signal transfer function in both stages. The chip reconfigures its loop filter order (either 2nd or 4th order), clock frequency (from 40 to 240 MHz) and scales power according to the required specifications for different wireless standards, covering: GSM, Bluetooth, GPS, UMTS, DVB-H and WiMAX. Measurements feature a dynamic range of 78/70/71.5/66/62/52dB and a peak signal-to-noise+distortion) ratio of 72.3/68.0/65.4/63.3/59.1/48.7dB within 100kHz/500kHz/1MHz/2MHz/4MHz/10MHz, while consuming 4.6/5.3/5.6/2/8/4/11mW, respectively. These results show a competitive performance with the state-of-the-art multi-standard ΣΔ modulators, covering one of the widest regions in the DR-vs.-Bandwidth plane.

Designing systems from concepts: a crucial engineering approach
Ludwig De Locht, Gerd Vandersteen, Yves Rolain, Greet Van de Perre, Mart Lybeert
EESD10, Engineering Education in Sustainable Development, Gothenburg, Sweden, September 19-22, 2010
Engineers need a systematic framework to design systems, since ad-hoc solutions are nearly always inferior when working towards a sustainable solution. The training to use a systematic design framework is often overlooked in the first years in engineering education, since the students are primarily confronted with small problems where ad-hoc solution seem time-saving. This paper presents an experience-based learning project for bachelor students in their fourth semester. They have to control the height of a ping-pong ball in a tube by controlling a variable speed fan and they also have to implement an interface to a PC using a microcontroller. They are guided to use a systematic system-level approach for the design of their system, but they keep the freedom to make their own implementation choices during the top-down design. The students gain plenty of engineering attitudes in designing systems and in control. They will automatically use these attitudes in other projects such that using good engineering practices become an automatism for them.

Noise Leakage Suppression in Multivariate FRF Measurements Using Periodic Excitations
R. Pintelon, G. Vandersteen, J. Schoukens, and Y. Rolain
Due to the non-periodic nature of noise, the steady state response of a dynamic system to a periodic input is still subject to noise transients (noise leakage errors). For lightly damped systems these noise transients (significantly) increase the variance of frequency response function (FRF) measurements [Pintelon MSSP10c]. This paper presents a method for suppressing the noise transients in FRF measurements using periodic excitations. It is based on a local polynomial approximation of the noise leakage error and is an extension of the results of [Pintelon MSSP10c] to multivariable systems. Compared with the local polynomial method for random excitations [Pintelon MSSP10a, Pintelon MSSP10b], no local polynomial approximation of the frequency response matrix is made. Irrespective of the number of inputs and outputs, it is shown in this paper that 2 periods of the state state response are enough to suppress the noise transients and to estimate the input-output noise covariance matrix. Since no distinction can be made between the system and noise transients, the presented method is also applicable to the first 2 periods of the transient response of the system to a periodic input. For lightly damped systems this results in a significant reduction of the measurement time.

Frequency Response Function measurements using concatenated data records
Johan Schoukens, Gerd Vandersteen, Rik Pintelon
This paper presents a nonparametric method to measure the frequency response function (FRF) of a linear dynamic system that allows a series of sub-records to be concatenated in one long data record without suffering from the leakage and transient errors. The method combines data blocks (of different length) into a single record, resulting in an increased frequency resolution. The analysis is based on the recent insight that leakage errors in the frequency domain have a smooth nature that is completely similar to that of inter transients in the time domain. The method is applicable to both single-input-single output (SISO) and multiple-input-multiple-output (MIMO) systems. The results are illustrated on simulations and experimental data.

**Estimation of the instantaneous impedance of time-varying systems**

E. Tourné, T. Breugelmans, J. Lataire, T. Hauffe, R. Pintelon, and A. Hubin  
Proceedings 61th Annual Meeting of the International Society of Electrochemistry, Nice (France), 26 September - 1 October 2010

Recently, an integrated electrochemical impedance method was introduced by our group to measure, analyze and model electrochemical systems. In a correct and reliable way [1,2]. With the current state-of-the-art, a necessary condition for reliable impedance data is that the system responds linearly to the perturbation signal and that it behaves stationary. The integrated method allows measure the impedance spectrum and to check whether these conditions are fulfilled, all from a single experiment. The method uses odd random phase multisines as excitation signals, which have been shown to have several advantages, e.g. a reduction of the measurement time. In many practical applications time-dependent variations may occur and in rapidly evolving systems (like corrosion), the reduction of the measurement time, may not be sufficient. The use of an odd random phase multisine excitation allows detecting this. However, detection of a non-stationary behavior is not enough. If we want to try to reduce the contribution of the non-stationarities by adapting the experimental conditions or take the influence of the non-stationarities into account when modeling, we should proceed one step further. In this paper it will be shown how the response of time-varying systems to multisines allows one to immediately distinguish the time invariant part from the time varying part by inspecting the output signal. Also, the response to the multisine excitation is used to estimate the evolution of the instantaneous impedance over the measured time window. The latter is defined as the impedance that one obtains by freezing the dynamics at some time instant. An estimate of the evolution of the instantaneous impedance provides valuable insight into the system. The method will be illustrated based on data obtained for different experimental systems: corrosion of a coated metal (aluminium AA2024 with a silane BTSE coating) and the formation of self assembling monolayers of phosphonic acids on aluminium oxide.9

**Evaluation of oxide growth and relation between electrolytic parameters during porous anodizing of aluminium in an extensive experimental range**

Proceedings 218th ECS Meeting, Las Vegas (USA), 10-15 October 2010.

The phenomenological characteristics of porous oxide films, formed by anodizing of aluminium, are well documented in the literature. In addition, various models are suggested for the microscopic transport mechanism prevailing in the oxide layer during growth. In contrast, models describing the dependency between general electrochemical parameters, such as current density, electrode potential and anodizing temperature, are rare. Nonetheless, due to the direct link between the anode potential and the dimensions of the characteristic features of the oxide, such as the barrier layer thickness and the pore and cell diameter, such models implicitly reflect the influence of the process parameters on the oxide micro structure. In addition, on a macroscopic scale these models enable calculating variations in local current density and anodizing temperature along aluminium electrodes during simulations of the anodizing process in various reactor geometries and process conditions.

**Nonlinear least-squares modeling of 3D interaction position in a monolithic scintillator block**

Zhi Li, M Wedrowski, P Bruyndonckx and G Vandersteen  

Here we present a study of possible models for monolithic scintillation crystals, to describe the relation between the scintillation light point-of-origin and the measured photo detector pixel signals, from which the coordinates in x, y and DOI coordinates can be estimated simultaneously by nonlinear least square fitting. The method only depends on the information embedded in the signals of individual events, and therefore does not need any prior position training or calibration. The general model consist of a constant background due to diffuse reflection on the reflector covering the scintillator block, a distribution representing direct detection of scintillation photons and virtual sources to take internal reflections on the side surface into account. Three possible distributions of the direct and virtual light sources were evaluated: an exact solid angle based distribution, an approximated solid angle distribution and an approximated solid angle based distribution including critical angle effects. The performance of the general model using these three distributions was studied using Monte Carlo simulated data of a 20x20x10 mm LSO block read out by 2 Hamamatsu S8550 APD arrays (8x8 pixels in total, 1.6 mm pixel size). The approximated solid angle based model had the best compromise between resolution (1.1 mm FWHM in X and Y direction, 2 mm FWHM DOI) and simplicity. The approximated solid angle model was also evaluated using experimental data by positioning a narrow 1.1 mm FWHM beam of 511 keV photons at known positions on the 20x20x10 mm LSO block. An average resolution in the X direction of 1.87 mm FWHM, including the effect of the beam size, was obtained for positions covering the complete block. The DOI resolution in the experimental set-up cannot be determined directly but using a photon beam impinging at 45 degree angle, we established a 3.4 mm FWHM upper limit of the DOI resolution.

**A 6.1 GS/s 52.8 mW 43 dB DR 80 MHz bandwidth 2.4 GHz RF Bandpass Delta Sigma ADC in 40nm CMOS**

J. Ryckaert, A. Geis, L. Bos, G. Van der Plas, and J. Craninckx  
A 2.4 GHz 4th order BP ADC is presented. The feedforward topology uses Gm-LC resonators that can be calibrated in frequency. The quantizer is split in 6 interleaved comparators to relax speed. Clocked at 6.1 GHz, it achieves a DR of 43 dB in 80 MHz consuming 52.8 mW. Implemented in 40 nm CMOS, it achieves a FoM of 3.6 pJ/conv. step, which is to date the lowest published value for RF BP ADCs.

**c784. Influence Of Feedback On The Mtc Estimate By Noise Analysis**
Griet Monteyne, Peter Baeten, Johan Schoukens
Proceedings of the 7th International Topical Meeting on Nuclear Plant Instrumentation, Control and Human-Machine Interface Technologies (NPIC&HMIT 2010), Las Vegas, Nevada, November 7-11, 2010, pp. 662-669
This article discusses the influence of feedback on the Moderator Temperature Coefficient (MTC) estimate by a noise analysis method. Until now feedback was considered to be negligible in the frequency band of interest. However measurements at a Belgian Nuclear Power Plant will be used to show that the influence of feedback on the MTC estimate is not negligible in the frequency band of interest. This makes the analysis difficult since the presence of feedback creates systematic errors in the MTC estimate unless special experimental conditions can be realized. The theoretical analysis will explain how the most used non-parametric estimation of the MTC is influenced by the presence of the feedback. For the explanation we will consider a simplified scheme of the MTC measurement setup with feedback. The theory will be verified by simulations in MATLAB. For the verification we consider a simplified system captured in a feedback loop. We will estimate the system for different situations. It will be seen that the non-parametric system estimate is only unbiased when the signal that is fed back to the input is negligible in comparison with the reference signal. Since the feedback is not negligible in practice, special experimental conditions are required to obtain an unbiased non-parametric MTC estimate.

**c785. Study Of The Precision Of The Mtc Estimate By Noise Analysis**
Griet Monteyne, Peter Baeten, Johan Schoukens
Proceedings of the 7th International Topical Meeting on Nuclear Plant Instrumentation, Control and Human-Machine Interface Technologies (NPIC&HMIT 2010), Las Vegas, Nevada, November 7-11, 2010, pp. 617-625
This paper will discuss the precision of the Moderator Temperature Coefficient (MTC) estimate by noise analysis. Until now all attention went to the discussion of the bias of the MTC estimate that is due to the use of a small number of temperature sensors. However the discussion of the precision of the estimate was neglected. We will study the relation between the relative precision, the measurement time and the coherence. Based on this relation rules of thumb will be given in order to estimate the required measurement time for a specified precision and a given measurement setup. We will explain how a low coherence results in a large standard deviation. Next it will be shown that the standard deviation can be decreased by increasing the measurement time. The theoretical analysis will be verified by simulations in MATLAB and measurements at a Nuclear Power Plant in Belgium. From the measurements it will be seen that in practice we expect a coherence of 0.1 at a frequency lower than 0.1Hz. This results in a measurement time of more than 9 days if we want to achieve a standard deviation of 1%. A standard deviation of 5% can be achieved with a measurement time larger than 11h. This indicates that low coherences can result in unrealistic measurement times during which the reactor has to stay stationary.

**c786. Parametric Frequency Domain Identification of a Time-Varying System as a Time-dependent Weighted Sum of Time-Invariant Systems**
John Lataire and Rik Pintelon
49th IEEE Conference on Decision and Control, Atlanta, GA, USA, December 15-17, 2010, pp. 2029-2034
A frequency domain, parametric identification procedure for single-input, single output time-varying systems is presented. The output of the model is built as a time-varying weighted sum of the responses of linear time-invariant systems. A judicious choice of the weighting functions is shown to provide an intuitive insight into the evolution of the instantaneous transfer function with time. Results of previous work are used to obtain non-parametric initial estimates of both the time-varying dynamics and the disturbing noise characteristics from the response of the system to a multisine excitation. The maximum likelihood estimator is set up and a minimization algorithm is developed. The estimator is applied to a simulation example and a measurement example (electronic circuit) which approximates the model assumptions.

**c787. On the Use of Parametric and Non-Parametric Noise-models in time- and frequency domain System Identification**
Johan Schoukens, Yves Rolain and Rik Pintelon
49th IEEE Conference on Decision and Control, Atlanta, GA, USA, December 15-17, 2010, pp. 316-321
In this paper we start from the observation that there is an exact equivalence between time- and frequency domain identification for finite length data records under the standard conditions of the prediction error framework. Next we study the identification of a nonparametric plant and noise model, in the time- and frequency domain. Finally we discuss the mixed use of parametric plant models and nonparametric noise models in the identification process, and comment its impact on the user choices. It turns out that the availability of a nonparametric noise model simplifies significantly the identification of a parametric plant model. All these results are valid for random, arbitrary, and periodic excitations.

**c788. Nuclear Norm Regularization for Overparametrized Hammerstein Systems**
Tillmann Falck, Johan A.K. Suykens, Johan Schoukens, Bart De Moor
4.5 ABSTRACTS (2010)

a212. Identification of Linear, Periodically Time-Varying Systems
Ebrahim Louarroudi, John Lataire, Rik Pintelon
29th Benelux Meeting on System and Control, Heeze, The Netherlands, March 30-1 April, 2010
In some applications the considered real-life systems do not satisfy the time invariant condition. For that reason it is convenient to extent the framework of LTI-systems to systems that might evolve over time. There exist a wide range of applications where the treatment of time-varying systems is indispensable (e.g. flight flutter analysis, pitting corrosion in metals, periodically time-varying robot, etc.). When the time variation is forced experimentally one can choose between periodically, arbitrary (non-periodically) or hold (piecewise constant variation) configurations for the external (scheduling) parameter(s). This article deals only with imposed external scheduling parameters that are periodically varying over time: we talk about Linear Periodically Time-Varying (LPTV) systems.

a213. Behavioral modeling of the thermal dynamics of borefields for geothermal applications
Griet Monteyne and Gerd Vandersteen
29th Benelux Meeting on System and Control, Heeze, The Netherlands, March 30-1 April, 2010
This work is related to geothermal heat pumps for central heating and/or cooling using geothermal energy. This is one of the most recommendable methods for heating buildings via so called green energy. Current controllers don't explicitly take the dynamic behavior of the source-side (the so called borefields in the ground) into account. The object of this work is to model the thermal dynamic behavior of the surrounding geology. This model can then be used to develop an optimal control strategy that also prevents the exhaustion of the heat from the soil on short and long term.

a214. Frequency Domain Total Least Squares Estimator of Time-Varying Systems
John Lataire, Rik Pintelon
29th Benelux Meeting on Systems and Control, Heeze, The Netherlands, March 30-1 April, 2010
In many engineering applications the assumption of time invariance is not fulfilled. Consider for instance the identification of the resonance frequency and the damping of the wings of a plane. These are functions of the light speed and the height and, thus, are time-varying while varying. The ability of identifying time-varying models on these kinds of systems is more than welcome. Contrary to most previous works (e.g. [3]), frequency domain methods are used. These have proven their usefulness in system identification for the efficient selection of a desired frequency band of interest and the ate identification of continuous-time linear models from sampled data in a band-limited measurement setup.

a215. Reduction of polynomial nonlinear state-space models by means of nonlinear similarity transforms
Anne Van Mulders, Laurent Vanbeylen, Johan Schoukens
29th Benelux Meeting on Systems and Control, Heeze, The Netherlands, March 30-1 April, 2010
Nowadays, there is a need for good quality nonlinear models. However, Polynomial Nonlinear State-Space models (PNLSS), which have quite good approximation capabilities, contain typically several hundreds of parameters. After identification of a PNLSS model, in general all parameters will be nonzero, while it is known that a very simple, sparse representation exists for Wiener-Hammerstein and nonlinear feedback systems. In this approach, we focus on reducing the number of parameters in the model, by using a property valid for such block-structured nonlinear systems: the nonlinear parameter matrix has a low rank. We impose this property by means of a re-parameterisation via singular value decomposition. A standard optimisation method can then be used to get a new parameter fit with fewer parameters.

a216. Estimation of the probability of stable operation over a given time interval for discrete-time nonlinear state-space models
Laurent Vanbeylen, Anne Van Mulders, Johan Schoukens
29th Benelux Meeting on Systems and Control, Heeze, The Netherlands, March 30-1 April, 2010
This work is concerned with determining the (un)stable behaviour of discrete-time nonlinear state-space models. For this kind of models, it may happen that the (in)stability properties depend on the nature of the (stochastic) input signal. E.g. the system can show a stable behaviour at low amplitudes, and an unstable behaviour at high amplitudes. In between, there can be a transition zone between low and high probabilities of instability. In the phase plane, this can be interpreted as a stable equilibrium in the neighbourhood of the origin (i.e. a bounded Region Of Attraction (ROA)) and the input disturbing the state in a random way. A low input amplitude causes the states to stay inside the ROA with high probability, while a large one may be more likely to push the state out of the ROA, and hence cause unstable operation with much higher probability. In this context, the user may ask him-/herself the question whether the given model will be likely to behave stably or not for a given class of input signals on a certain time interval $t = 0,...,T$, and starting at a given initial state. This work allows the user to answer this question, in the case of a normally distributed input disturbance with a small variance and with an arbitrary power spectrum provided by the user. The state transition function, of the type $x(t+1) = f(x(t),u(t))$, and its derivatives have to be known. The probability density function (pdf) of the state at the provided time instant $T$ can be approximated at every point of the state space via the Laplace integration method. This in turn requires the solution of a constrained optimization problem.

After integration of the state pdf over a domain, one obtains the probability that the state has remained inside this domain. Taking the domain equal to the ROA yields the probability of stable operation until time instant $T$. The method is illustrated by means of a simple example.

**a217. Estimating nonlinear dynamics in nonlinear state-space models**

Anna Marconato, Jonas Sjöberg, Johan Schoukens, Johan Suykens
29th Benelux Meeting on Systems and Control, Heeze, The Netherlands, March 30-1 April, 2010

This work aims at developing methods for estimating nonlinear state-space models of the form:

$$x(t + 1) = f(x(t),u(t)) \quad (1)$$

$$y(t) = g(x(t))$$

based on a combination of ideas from the statistical learning community used to solve nonlinear regression problems on one hand, see e.g. [1] and [2], and methods to handle dynamics from the system identification community on the other hand. The approach targets systems which are fairly well approximated by linear models. The proposed method consists of the following steps:

- model the dynamics of the system
- estimate the nonlinear states
- model the nonlinearities.

**a218. Good short record confidence regions for system identification**

Kurt Barbé, Johan Schoukens
29th Benelux Meeting on Systems and Control, Heeze, The Netherlands, March 30-1 April, 2010

**a219. Accurate Oscillometric Blood Pressure Measurement: an Experimental Approach**

Kurt Barbé, Wendy Van Moer, Lieve Lauwers and Danny Schoors
29th Benelux Meeting on Systems and Control, Heeze, The Netherlands, March 30-1 April, 2010

**a220. Estimation of the probability of stable operation over a given time interval for discrete-time nonlinear state-space models**

Laurent Vanbeylen, Anne Van Mulders, Johan Schoukens
PhD Research Day, Vrije Universiteit Brussel, Brussels, May 28, 2010

This work is concerned with determining the (un)stable behaviour of discrete-time nonlinear state-space models. For this kind of models, it may happen that the (in)stability properties depend on the nature of the (stochastic) input signal. E.g. the system can show a stable behaviour at low amplitudes, and an unstable behaviour at high amplitudes. In between, there can be a transition zone between low and high probabilities of instability. In the phase plane, this can be interpreted as a stable equilibrium in the neighbourhood of the origin (i.e. a bounded Region Of Attraction (ROA)) and the input disturbing the state in a random way. A low input amplitude causes the states to stay inside the ROA with high probability, while a large one may be more likely to push the state out of the ROA, and hence cause unstable operation with much higher probability. In this context, the user may ask him-/herself the question whether the given model will be likely to behave stably or not for a given class of input signals on a certain time interval $t = 0,...,T$, and starting at a given initial state. This work allows the user to answer this question, in the case of a normally distributed input disturbance with a small variance and with an arbitrary power spectrum provided by the user. The state transition function, of the type $x(t+1) = f(x(t),u(t))$, and its derivatives have to be known. The probability density function (pdf) of the state at the provided time instant $T$ can be approximated at every point of the state space via the Laplace integration method. This in turn requires the solution of a constrained optimization problem.

After integration of the state pdf over a domain, one obtains the probability that the state has remained inside this domain. Taking the domain equal to the ROA yields the probability of stable operation until time instant $T$. The method is illustrated by means of a simple example.

**a221. Periodic time-series modeling with guaranteed positive growth rate estimation for environmental records**

Veerle Beelaerts, Bauwens M, Versteegh EAA, Pintelon R and Dheurs F - 2nd Sclerocronology Conference, 24-28 July 2010, Mainz, Germany.
Proxies are measured on a distance scale, mostly along the maximum growth axis. Since all environmental archives grow at different speeds, and since the growth rate varies during the life-time. In space, different proxy records need a common axis, for example a time axis on which they can be compared. A number of methods which estimate a time axis are described in literature (Martinson et al. 1982 J. Geophys. Res. 87, 4807-4818; Paillard et al. 1996 EOS Trans. 77, 379; Yu and Ding 1998 Geophys. Res. Lett. 25, 4525-4528; Lisiecki and Lisiecki 2002 Paleoceanog. 17, doi: 10.1029/2001PA000733; Goodwin et al. 2009 Palaeogeogr. Palaeoclimatol Palaeoecol. 276, 47-55; Brüggeman 1992 Paleoceanog. 7, 476-487; Wilckinson and Ivany 2002 Palaeogeogr. Palaeoclimatol Palaeoecol. 185, 95-114; de Ridder et al. 2004 Geochem. Geophys. Geosyst. 5, doi: 10.1029/2004GC000771; de Brouwere et al. 2008 Computer Geosci. 34, 1781-1790 ; Beelaerts et al. 2010 Math. Geosci., in press). The methods described in de Brouwere et al. (2008 Computer Geosci. 34, 1781-1790) and Beelaerts et al. (2010 Math. Geosci., in press) are parametric signal model methods, which assume that the signal on a time scale is harmonic. In these methods, the unconstrained identification of the proposed signal model chooses the best parameters irrespective of the order of the data observations. In other words, subsequent observations can be inverted on the time axis. Both methods are especially vulnerable to this artifact when the number of phase distortion parameters is relatively high and thus when the noise sensitivity is larger. In de Brouwere et al. (2008 Computer Geosci. 34, 1781-1790) a method, the time inversion constraint method, is described which corrects these time inversions by including inequality constraints on the phase distortion parameters Fletcher 1991 Practical Methods of Optimization, Wiley). For large violations against the order of the time instances, the number of constraints becomes larger than the number of parameters, and consequently, the method becomes unfeasible. The aim of this work is to impose the positivity of the growth rate with a reduced number of linear constraints on the signal model parameters. The new method is compared to the time inversion constraint method and its noise sensitivity is tested on by means of a Monte-Carlo simulation. The usefulness of the method is demonstrated on the measurement of the vessel density, in a mangrove tree, Rhizophora mucronata, and the measurements of the Mg/Ca ratio, in a bivalve, Mytilus trossulus.

### Which proxies should be integrated in a multi-proxy model?

Maite Bawens, Veerle Beelaerts, Frank Dehairs and Johan Schoukens

2nd International Scler-chronology Conference, Mainz, Germany, 24-28th July 2010

All potential temperature proxies (e.g. δ18O, Mg, Sr,…) suffer of one common problem: the proxy signal is strongly influenced by non-temperature forcers such as salinity, metabolism and shell growth. The use of multi-proxy models offers a solution for that problem. However, the use of classical linear multiple regression models are not always appropriated since some data show substantial non-linear relationships between temperature and elemental ratios. In previous research we demonstrated that the so called Weight Determination by Manifold Regularization approach can be used to develop a non-linear multi-proxy model. Now a new question rise: “Which proxies should be integrated in the multi-proxy model?” We evaluated four trace element records (Mg/Ca, Sr/Ca, Ba/Ca and Pb/Ca) measured in the shell of the common mussel Mytilus edulis. Different proxy combinations were evaluated over a salinity range between 15 and 32. Our findings highlight Mg/Ca ratios as the most powerful paleothermometers but we indicate that its reconstruction performance is significantly improved by combining it whit other elemental ratios into a multi-proxy model. We assume that disturbances on Mg/Ca profile due to growth and food availability can be explained by sea surface temperature variations in the Sr/Ca profile and the Ba/Ca profile, which results in better temperature reconstructions using a Mg/Ca, Sr/Ca and Ba/Ca the WDMR. Although Pb/Ca ratios seem to contribute slightly positive to the final reconstruction performance of a four proxy model, we discourage the use of Pb/Ca in a multi-proxy model for temperature reconstruction since the element is known to be strongly influenced by antropogenetic forcers. Using Mg/Ca, Sr/Ca and Ba/Ca the WDMR model gave a mean squared error of ±2.21°C for a temperature reconstruction based on a shell sampled independently in time and location.

### 4.6 WORKSHOPS (2010)

#### Linearizing oscillometric blood pressure measurements: (non)sense?

Kurt Barbé and Wendy Van Moer

Poster presentation at IUAP/PAI DYSCO study day, Gent, het Pand, May 31st, 2010

The oscillometric waveform measured by automatic non-invasive blood pressure meters (NIBP) is analyzed by transforming the data from the time domain to the frequency domain. This Fourier analysis reveals that the measured blood pressure signals are heavily disturbed by nonlinear contributions. Classical blood pressure algorithms are based on the envelop of the measured blood pressure waveform. Due to the nonlinear contributions, calculating this envelope is not a self-evident task. The following question is answered: Are nonlinear contributions a significant source of information to compute the systolic and diastolic blood pressure?

#### Reduction of polynomial nonlinear state-space models

Anne Van Mulders, Laurent Vanbeylen and Johan Schoukens

Poster presentation at IUAP/PAI DYSCO study day, Gent, het Pand, May 31st, 2010

Nowadays, there is a need for good quality nonlinear models. However, Polynomial Nonlinear State-Space models (PNLSS), which have quite good approximation capabilities, contain typically several hundreds of parameters. After identification of a PNLSS model, in general all parameters will be nonzero, while it is known that a very simple, sparse representation exists for Wiener-Hammerstein and nonlinear feedback systems. In this approach, we focus on reducing the number of parameters in the model, by using a property valid for such block-structured nonlinear systems: the nonlinear parameter matrix has a low rank. We impose this property by means of a re-parameterisation via singular value decomposition. A standard optimisation method can then be used to get a new parameter fit with fewer parameters.

#### Estimating nonlinear dynamics in nonlinear state-space models
Parametric identification of parallel Hammerstein and parallel Wiener systems

Maarten Schoukens, Yves Rolain
ERSNI Workshop Cambridge, UK, September 26-29, 2010

This poster proposes a parametric identification method for parallel Hammerstein and parallel Wiener systems. In this modelling approach, the static nonlinearities are represented by a linear combination of basis functions, and the linear dynamic systems by a parametric rational function in the z-domain. A three step identification procedure is used to obtain a set of starting values for the parameters. In the first step, the FRF of the best linear approximation is estimated for different input excitation levels. In the second step, the varying dynamics are decomposed over a number of parallel branches using a singular value decomposition (SVD) of the combined dynamic behaviour. In the last step, the static nonlinearities are estimated using a linear least squares estimation. In the case of parallel Hammerstein systems this results in one nonlinear function for each branch of the model. For parallel Wiener systems one nonlinear function with multiple inputs and a single output is obtained. Furthermore an iterative identification

Nonparametric preprocessing in system identification. A powerful tool
Johan Schoukens
ERSNI Workshop Cambridge, UK, September 26-29, 2010

This work aims at developing methods for estimating nonlinear state-space models of the form
\[ x(t+1) = f(x(t), u(t)) \]
\[ y(t) = g(x(t)) \]

based on a combination of ideas from the statistical learning community used to solve nonlinear regression problems on one hand, and methods to handle dynamics from the system identification community on the other hand. The proposed approach consists of the following steps: (1) model the dynamics of the system based on the concept of best linear approximation; 2) estimate the nonlinear states by solving a least squares problem; 3) model the nonlinearities by using regression methods such as Neural Networks and Support Vector Machines.

Modeling and identification of distillation columns using optimized excitations.
Diana Uglyumova and Gerd Vandersteen
ERSNI Workshop Cambridge, UK, September 26-29, 2010

The aim of this research is to enhance the performance of a distillation column through a better modeling and control strategy. This is done by optimizing the different accessible inputs of the column and by improving the system identification techniques used. A distillation column is, as such, a highly non-linear Multiple-Input Multiple-Output (MIMO) system that suffers from drift, due to changes of e.g. the environment temperature, and long transient effects, due to huge time constants in the column. In addition, specific constraints on the excitations and operation of the distillation column have to be taken into account. This implies that practical identification techniques should be robust to non-linearity and drift, overriding the applied excitation (for safety reasons) and possible missing data. The starting point is to use (orthogonal) multisine excitations for MIMO systems. These excitations make it possible to remove transients and to separate the additive (measurement) noise from the non-linearities. Using these excitations, the so-called Local Polynomial (LP) method is used to determine a non-parametric model for the linear behavior and the additive noise covariance matrix. This method also enables the identification of the so-called Best Linear Approximation (BLA) of the distillation column. The non-parametric model is then used to extract a rational model in the Laplace-domain with a delay term. This model can be used for the design of a model predictive controller (MPC) for the distillation column. Measurements from a pilot binary distillation column at KUL-BioTeC are available and will be used to verify the results. In a later stage of the research, all the mentioned identification techniques will be extended to enable the modeling and control of periodically forced distillation columns.

Estimating nonlinear dynamics in nonlinear state-space models
Anna Marconato, Jonas Sjoberg, Johan Schoukens, Johan Suykens
ERSNI Workshop Cambridge, UK, September 26-29, 2010

This work aims at developing methods for estimating nonlinear state-space models of the form
\[ x(t+1) = f(x(t), u(t)) \]
\[ y(t) = g(x(t)) \]

based on a combination of ideas from the statistical learning community used to solve nonlinear regression problems on one hand, and methods to handle dynamics from the system identification community on the other hand. The proposed approach consists of the following steps: (1) model the dynamics of the system based on the concept of best linear approximation; 2) estimate the nonlinear states by solving a least squares problem; 3) model the nonlinearities by using regression methods such as Neural Networks and Support Vector Machines.

Frequency domain total least squares estimator of linear, time-varying systems
John Lataire and Rik Pintelon
ERSNI Workshop Cambridge, UK, September 26-29, 2010

A frequency domain total least squares estimator is presented for identifying linear, continuous-time, time-varying dynamic systems. The model considered is a linear, ordinary differential equation whose coefficients vary as polynomials in time. It is shown that the bias errors due to windowing and sampling the continuous-time signals can be modelled by a polynomial function of the frequency. The regression matrices of the estimators are shown to be computed efficiently using the Fast Fourier Transform algorithm and its inverse. The proposed total least squares estimator is easily implemented, but it is inconsistent. By taking into account the noise information, further development yields the generalised total least squares and a weighted, nonlinear least squares estimator, for which consistency can be proven. The estimators are illustrated on simulation and measurement data.

Nonparametric preprocessing in system identification. A powerful tool
Johan Schoukens
Tutorial at ERNSI Workshop Cambridge, UK, September 26-29, 2010

This work aims at developing methods for estimating nonlinear state-space models of the form
\[ x(t+1) = f(x(t), u(t)) \]
\[ y(t) = g(x(t)) \]

based on a combination of ideas from the statistical learning community used to solve nonlinear regression problems on one hand, and methods to handle dynamics from the system identification community on the other hand. The proposed approach consists of the following steps: (1) model the dynamics of the system based on the concept of best linear approximation; 2) estimate the nonlinear states by solving a least squares problem; 3) model the nonlinearities by using regression methods such as Neural Networks and Support Vector Machines.
scheme is introduced to further reduce the model errors. This iterative scheme alternately estimates updated parameters for the linear dynamic systems and the static nonlinearities that are present in the parallel Hammerstein and parallel Wiener systems starting from the initial three step estimates. The iterative method is fully implemented for the parallel Hammerstein systems, but is still work in progress for the case of parallel Wiener systems. The method is illustrated on a series of simulations and experiments, both for the parallel Hammerstein and parallel Wiener case.

w135. **Parametric Frequency Domain Estimator for Linear, Periodically Time-Varying Systems**

Ebrahim Louarroudii

ERSNI Workshop Cambridge, UK, September 26-29, 2010

Although linear time-invariant (LTI) models cover a broad range of applications in practice, there are still cases where the time-invariant condition does not hold. Time-varying systems, in particular periodically time-varying, could be found in a lot of engineering applications such as biochemical processes, mechanical systems and electronic circuits. Consider for instance mechanical structures that are subject to increasing damage, pitting corrosion of metals, metal deposition, biological systems or even time-invariant systems with a time-varying setpoint. All these examples cannot be treated in the classical LTI framework. So an extension of the classical framework is needed. The class of systems considered in this poster, is assumed to be well described by ordinary differential equations with coefficients that vary periodically over time, making use of multisines both for excitations as well as for the system parameters. Moreover, we also assume that the fundamental period of the excitation is equal to a multiple number of the period of the system parameters. The major contribution of this poster is about the construction of a parametric frequency domain estimator for periodically time-varying systems. This estimator is illustrated on a real-life time-varying system (an electronic circuit).

w136. **Comparison of heat diffusion model in Laplace and Warburg variable**

Griet Monteyne, Gerd Vandersteen

ERSNI Workshop Cambridge, UK, September 26-29, 2010

The modeling of heat diffusion is important, for example, for the development of an efficient control strategy of a geothermal heat pump. Heat diffusion processes are typically described by parabolic partial differential equations, leading to transfer functions that can be described as rational transfer functions in the Warburg variable $s$. Small thermal structures, on the other hand, are often modeled as a series of connected RC networks. This poster discusses these two different rational transfer function models used for the dynamic modeling of a simple heat diffusion problem. The heat diffusion in an isolated iron construction is considered as a test case. A comparison is made between the modeling using rational transfer function models in the Laplace variable $s$ and in the Warburg variable $\gamma s$. First, a rational model in the Laplace domain is fitted on the measured data. By limiting the possible rational models to the ones for which the poles and zeros are real we find a model that can be interpreted as a combination of resistors and capacitors. Since diffusion phenomena can only be approximately described by a rational form in the $s$-domain we also fit a rational model in the $\gamma s$-domain. Then we try to interpret model in the $\gamma s$-domain as a combination of two rational models, namely one in the $s$-domain and one in the $\gamma s$-domain. The first model in the $s$-domain describes the heat transport over a short distance whereas the latter model in the $\gamma s$-domain describes the heat diffusion over large distances. Finally, we compare the results in both domains in order to choose the best suited model.

w137. **Modeling and identification of distillation columns using optimized excitations**

Diana Ugryumova and Gerd Vandersteen

Presentation of poster at the IUAP/PAI DYSCO workshop, Louvain-la-Neuve, Château-Ferme de Profondval, 28-29 October 2010

The aim of this research is to enhance the performance of a distillation column through a better modeling and control strategy. This is done by optimizing the different accessible inputs of the column and by improving the system identification techniques used. A distillation column is, as such, a highly non-linear Multiple-Input Multiple-Output (MIMO) system that suffers from drift, due to changes of e.g. the environment temperature, and long transient effects, due to huge time constants in the column. In addition, specific constraints on the excitations and operation of the distillation column have to be taken into account. This implies that practical identification techniques should be robust to non-linearities and drift, overcoming the applied excitation (for safety reasons) and possible missing data. The starting point is to use (orthogonal) multisine excitations for MIMO systems. These excitations make it possible to remove transients and to separate the additive (measurement) noise from the non-linearities. Using these excitation, the so-called Local Polynomial (LP) method is used to determine a non-parametric model for the linear behavior and the additive noise covariance matrix. This method also enables the identification of the so-called Best Linear Approximation (BLA) of the distillation column. The non-parametric model is then used to extract a rational model in the Laplace-domain with a delay term. This model can be used for the design of a model predictive controller (MPC) for the distillation column. Measurements from a pilot binary distillation column at KUL-BioTeC are available and will be used to verify the results. In a later stage of the research, all the mentioned identification techniques will be extended to enable the modeling and control of periodically forced distillation columns.

w138. **Parametric identification of parallel Hammerstein and parallel Wiener systems**

Maarten Schoukens, Yves Rolain

Presentation of poster at the IUAP/PAI DYSCO workshop, Louvain-la-Neuve, Château-Ferme de Profondval, 28-29 October 2010

This poster proposes a parametric identification method for parallel Hammerstein and parallel Wiener systems. In this modelling approach, the static nonlinearities are represented by a linear combination of basis functions, and the linear dynamic systems by a parametric rational function in the $z$-domain. A three step identification procedure is used to obtain a set of starting values for the parameters. In the rst step, the FRF of the best linear approximation is
estimated for different input excitation levels. In the second step, the varying dynamics are decomposed over a number of parallel branches using a singular value decomposition (SVD) of the combined dynamic behaviour. In the last step, the static nonlinearities are estimated using a linear least squares estimation. In the case of parallel Hammerstein systems this results in one nonlinear function for each branch of the model. For parallel Wiener systems one nonlinear function with multiple inputs and a single output is obtained. Furthermore an iterative identification scheme is introduced to further reduce the model errors. This iterative scheme alternately estimates updated parameters for the linear dynamic systems and the static nonlinearities that are present in the parallel Hammerstein and parallel Wiener systems starting from the initial three step estimates. The iterative method is fully implemented for the parallel Hammerstein systems, but is still work in progress for the case of parallel Wiener systems. The method is illustrated on a series of simulations and experiments, both for the parallel Hammerstein and parallel Wiener case.

4.7 PRESENTATIONS ORGANISED BY THE DEPT. ELEC (2010)

4. Frequency domain Total Least Squares Estimator of Time-Varying Systems
John Latera, VUB-ELEC, March 24, 2010
A frequency domain total least squares estimator is presented for identifying linear, continuous-time, time-varying dynamic systems. The model considered is a linear, ordinary differential equation whose coefficients vary as polynomials in time. It is shown that the bias errors due to windowing and sampling the continuous-time signals can be modelled by a polynomial function of the frequency. The regression matrices of the estimators are shown to be computed efficiently using the Fast Fourier Transform algorithm and its inverse. The proposed total least squares estimator is easily implemented, but it is inconsistent. By taking into account the noise information, further development yields the generalised total least squares and a weighted, nonlinear least squares estimator, for which consistency can be proven. The estimators are illustrated on simulation and measurement data.

5. Estimation of the probability of stable operation over a given time interval for discrete-time nonlinear state-space models
Laurent Vanbeylen, VUB-ELEC, April 16, 2010
This work is concerned with determining the (un)stable behaviour of discrete-time nonlinear state-space models when excited with a random input signal. For this kind of models, it may happen that the (in)stability properties depend on the stochastic nature of the random input. Knowing the power spectrum of the normally distributed driving random input u(t), and the analytic knowledge of the state evolution x(t+1)=f(x(t),u(t)) and the initial state x(0), the probability density function of the state x(T) at some later time instant T can be approximated via the Laplace integration method. Integration over an estimate of the region of attraction, yields the probability of stable operation from time instant 0 till time instant T.

6. Optimal experiment design for open and closed loop identification
Michel GEVERS, Université catholique de Louvain (CESAME), May 19, 2010
Optimal experiment design for system identification was a very active research topic in the 1970’s: the results at that time focused on the minimization of different measures of the parameter covariance matrix. The research on this topic disappeared from the horizon for more than a decade. In the mid eighties new results became available that focused on quality criteria that took account of the objective for which the model was estimated. These results were based on approximate variance formulae for the estimated transfer functions, under the assumption that the model order goes to infinity. Experiment design experienced a sudden revival of activity from around 2003 under a triple influence: the advent of new expressions for the variance of estimated quantities that did not require an assumption of model order going to infinity, the introduction of the concept of « least costly identification design », and the development of new optimal design techniques for identification that convert the optimization problem into semi-definite programs that can be solved using Linear Matrix Inequalities. In this talk we shall first review the development of optimal experiment design. We shall then present new results that allow one to solve the optimal closed loop experiment design problem, where the optimization is performed jointly with respect to the controller and the spectrum of the external excitation. Our results are based on the partial positive definite matrix completion theorem.

7. An introduction to Model Predictive Control for Automotive Applications
Paolo Falcone, Department of Signals and Systems, Chalmers University of Technology, Sweden, May 20, 2010
In Model Predictive Control (MPC), a model of the plant is used to predict the future evolution of the system. Based on this prediction, every time step a performance index is optimized (under operating constraints) with respect to a sequence of future control inputs in order to achieve the control objective. The first element of such optimal sequence is the control action applied to the plant at time \( t \). At time \( t+1 \), a new optimization is solved over a shifted prediction horizon. Even though MPC is recognized as one of the most powerful and effective techniques for controlling /multivariable/ /nonlinear/ plants with /constraints/, for decades its application has been restricted to "slow" systems. Parallel advances in theory and computing systems have enlarged the range of applications where real-time Nonlinear MPC can be applied. Yet, for a wide class of "fast" applications, the computational burden of Nonlinear MPC is still a serious barrier in its implementation. In this seminar we will illustrate basics MPC formulations and fundamental results. We will then show computational schemes aiming at reducing the online computational complexity. Examples in the automotive control field will be presented, where a Nonlinear MPC problem is formulated and solved in real-time for autonomously steering and braking a vehicle along a predefined path. Experimental results will show how MPC strategies can be used to orchestrate up to five control inputs to stabilize a vehicle up to 70 km/h in an autonomous double lane change on icy surfaces.

8. **Nonlinear system identification as a tool for investigating neuromuscular control systems**
   David Westwick, Department of Electrical and Computer Engineering University of Calgary, Calgary, Alberta, Canada, May 21, 2010

9. **The Intelligent Greenhouse**
   Peter Eredics, Department of Measurement and Information Systems Budapest University of Technology and Economics Budapest, Hungary, May 26, 2010
   The presentation introduces a new approach to greenhouse control based on artifical intelligence methods. The intelligent solution is expected to overcome the main limitations of the traditional greenhouse control, namely its dependence on manually set system parameters, the reactive nature of such systems and the missing synchronization of these actuators. The whole proposed control solution is outlined, with the introduction of the implemented measurement, control and monitoring subsystems.

10. **Film Bulk Acoustic Resonators Modeling**
    Mohamed Reda Amin El Barkouky, VUB-ELEC, June 1, 2010

11. **3D interaction position estimation in a monolithic scintillator block in Positron Emission Tomography**
    Zhi Li, VUB-ELEC, June 4, 2010
    The presentation is about a study of possible models for monolithic scintillation crystals, to describe the relation between the scintillation light point-of-origin and the measured photo detector pixel signals, from which the coordinates in x, y and depth-of-interaction (DOI) coordinates can be estimated simultaneously by nonlinear least-square fitting. The method only depends on the information embedded in the signals of individual events, and therefore does not need any prior position training or calibration. Current results and problems will be presented.

12. **Using Mathematica for research in System and Control area**
    Jonas Sjoberg, on sabbatical at VUB-ELEC, Chalmers University, Dept. Signals and Systems, June 6, 2010
    Most people in our research area use Matlab as their major tool in research. This talk demonstrates Mathematica as an alternative. After a short introduction of the main principles of Mathematica, the talk focus on the differences between the platforms. Examples of functionality which could motivate, at least temporary, to switch Mathematica are given.

13. **Nonlinear System Identification, on Algorithms Finding Initial Parameter Values for the Iterative Minimization of the Cost Function**
    Jonas Sjoberg, on sabbatical at VUB-ELEC, Chalmers University, Dept. Signals and Systems, July 1, 2010
    Computing the parameter estimate in a Maximum Likelihood system identification problem typically leads to an iterative minimization of the negative log-likelihood function. Only for models which are linear in the parameters one can be sure of avoiding local minima. A good start value for the iterative minimization decreases the risk of being trapped in a local minima. This talk starts with a tutorial part explaining the described problem in some detail. Examples are given on earlier work on algorithms for obtaining initial estimates for linear models such as ARMAX and state space models. We then turn to nonlinear system identification. Initialization of nonlinear black-box models using incremental models is explained and motivated. Algorithms for the traditional nonlinear structures Hammerstein and Wiener models are covered and a new algorithm for initializing Wiener-Hammerstein models is presented. This new algorithm is based on the benchmark data from SYSID 2009 and the result is analyzed and explained.

14. **Time series reconstruction of environmental proxy records**
    Veerle Beelaerts, VUB-ELEC, November 24, 2010
    Proxies are sources of climate information which are stored in natural archives. Since climate models are matched to proxies, proxies need to be as precise and as accurate as possible; otherwise the models, as well as the conclusions drawn, will be biased. In other words, the proxy data need to be treated in order to eliminate possible errors. This thesis focuses on in the preprocessing step of proxy data. Three problems are addressed here:
    Problem 1: Growth anomaly. Each data record therefore has its unique non-constant accretion rate and thus its own nonlinear distance–time relationship. Natural archives are sampled on a distance grid along their accretion axis. Starting from these distance series, a time series needs to be constructed, as comparison of different data records is only meaningful on a time grid.
Problem 2: Averaging. A typical example of sampling solid substrates, is drilling. As a result of the dimensions of the
drill, the holes drilled will not be infinitesimally small. Consequently, samples are not taken at a point in distance, but
rather over a volume in distance. This holds for most sampling methods in solid substrates. Thus, when the
continuous proxy signal is sampled, it will be averaged over the volume of the sample(Goodwin et al.,
2003)(Goodwin et al., 2003)(Goodwin et al., 2003)(Goodwin et al., 2003)(Goodwin et al., 2003)(Goodwin et al.,
2003).
Problem 3: Discretization errors. Some discretization errors will be present in the measured proxy record. This means
that the real maxima and minima might not be measured, because only a limited number of samples are taken.

4.8 PATENTS

1. TDR Based Transfer Function Estimation of Local Loop
   Tom Bostoen, Patrick Boets, Leo Van Biesen, Thierry Pollet and Mohamed Zekri
   European Patent Office, Application No./Patent No. 01400832.0-1246

2. Method and Apparatus for Identification of an Access Network by Means of 1-Port
   Measurements
   Tom Bostoen, Thierry Pollet, Patrick Boets, Mohamed Zekri and Leo Van Biesen

3. Method and Apparatus for Identification of an Access Network by Means of 1-Port
   Measurements
   Tom Bostoen, Thierry Pollet, Patrick Boets, Mohamed Zekri and Leo Van Biesen

4. Method for Matching an Adaptive Hybrid to a Line
   Tom Bostoen, Patrick Boets, Leo Van Biesen and Thierry Pollet
   European Patent Application, Application No./Patent No. 03292891.3

5. Interpretation system for interpreting reflectometry information
   T. Vermeiren, Tom Bostoen, Leo Van Biesen, Frank Louage, Patrick Boets

6. Interpretation system for interpreting reflectometry information
   T. Vermeiren, Tom Bostoen, Leo Van Biesen, Frank Louage, Patrick Boets

7. Localisation of Customer Premises in a Local Loop Based on Reflectometry Measurements
   Tom Bostoen, Thierry Pollet, Patrick Boets, Leo Van Biesen

8. Localisation of Customer Premises in a Local Loop Based on Reflectometry Measurements
   Tom Bostoen, Thierry Pollet, Patrick Boets, Leo Van Biesen

   Tom Bostoen, Thierry Pollet, Patrick Boets, Leo Van Biesen

10. Signal Pre Processing for Estimating attributes of transmission Line
    Tom Bostoen, Thierry Pollet, Patrick Boets, Leo Van Biesen

11. A method for determining bit error rates
    Vandersteen Gerd, Verbeeck Jozef, Rolain Yves, Schoukens Johan, Wambacq Piet, Donnay
    Stephane

12. A method for determining signals in mixed signal systems
    Wambacq Piet, Vandersteen Gerd, Rolain Yves, Dobrovolny Petr
4.9 DOCTORAL DISSERTATIONS

PhD1. Etude de la Production et des Conditions de Propagation d’On _ des de Choc Créés par un Plasma de Décharge
Jean Renneboog
Doctoral Dissertation, Université Libre de Bruxelles, 1967
Promoter: P. Baudoux (ULB)

PhD2. Bijdrage tot het Verweken en Meten van Nauwkeurig Bepaalde Fazeverschuivingen
Alain Barel
Doctoral Dissertation, Vrije Universiteit Brussel, April 1976
Judging-committee: G. Maggetto (VUB), Verlinden (VUB), Hoffman (RUG), C. Eugène (UCL)
Promoter: J. Renneboog (VUB)

PhD3. Maximum Informatie Extractie door middel van een Optimaal Frequentie Domein Experiment
Guy Vilain
Doctoral Dissertation, Vrije Universiteit Brussel, March 1983
Judging-committee: G. Maggetto (VUB), A. Barel (VUB), J. Cornelis (VUB), C. Eugène (UCL), Kerkhof, J. Vereecken (VUB), G. Vansteenkiste (VUB)
Promoter: J. Renneboog (VUB)

PhD4. Foutdetectie op Electrische Lijnen met behulp van een Digitale Behandeling van het Reflectogram
Leo Van Biesen
Doctoral Dissertation, Vrije Universiteit Brussel, April 1983
Judging-committee: G. Maggetto (VUB), A. Barel (VUB), Baert (RUG), C. Eugène (UCL), Goossens, Kirschvinck, J. Tiberghien (VUB)
Promoter: J. Renneboog (VUB)

PhD5. Parameterestimatie in Lineaire en Niet-Lineaire Systemen met Behulp van Digitale Tijdsdomein Metingen
Johan Schoukens
Doctoral Dissertation, Vrije Universiteit Brussel, February 1985
Judging-committee: G. Maggetto (VUB), A. Barel (VUB), P. Eykhoff (TU Eindhoven), C. Eugène (UCL), Hoffman (RUG), Spreet (RUG), O. Steenhaut (VUB), G. Vansteenkiste (VUB)
Promoter: J. Renneboog (VUB)

PhD6. Active Microstrip Antennas
Russell Dearnly
Doctoral Dissertation, Vrije Universiteit Brussel, June 1987
Judging-committee: G. Maggetto (VUB), L.P. Ligthart (TU Delft), G. Szymanski (Tech. University of Poznan), J. Tiberghien (VUB), A. Van De Capelle (KUL)
Promoters: J. Renneboog (VUB), A. Barel (VUB)

PhD7. Analysis and Application of a Maximum Likelihood Estimator for linear Systems
Rik Pintelon
Judging-committee: G. Maggetto (VUB), A. Barel (VUB), P. Eykhoff (TU Eindhoven), A. van den Bos (TU Delft), J. Vandewalle (KUL)
Promoters: J. Renneboog (VUB), J. Schoukens (VUB)

PhD8. Time Division Multiplexing in Optical Fiber Networks
Danny Sevenhans
Doctoral Dissertation, Vrije Universiteit Brussel, June 1988
Judging-committee: G. Maggetto (VUB), P. Kool (VUB), E. Stijns (VUB), R. Blondel (Université de Mons), P. Bulteel (Atea), C. Eugène (UCL), Baert (RUG)
Promoters: J. Renneboog (VUB), A. Barel (VUB)

PhD9. Design of Optimal Input Signals with Minimal Crest Factor
Edwin Van der Ouderaa
Judging-committee: G. Maggetto (VUB), F. Delbaen (VUB), P. Eykhoff (TU Eindhoven), R. Pintelon (VUB), J. Renneboog (VUB), A. van den Bos (TU Delft), J. Vandewalle (KUL)
Promoter: J. Schoukens (VUB)
PhD10. **Channel Multiple Access Protocols for a Hydrological Multihop Packet Radio Network**  
Thomas J. Odhiambo Afullo  
Doctoral Dissertation, Vrije Universiteit Brussel, June 1989  
Judging-committee: G. Maggetto (VUB), L. Van Biesen (VUB), J. Tiberghien (VUB), P. Van Binst (VUB), A. Van Der Beken (VUB)  
Promoter: A. Barel (VUB)

PhD11. **Steady-State Analysis of Strongly Nonlinear Circuits**  
Eli Van Den Eijnde  
Promoter: J. Schoukens (VUB)

PhD12. **Knowledge-Based Spectral Estimation**  
James Ambani Kulubi  
Judging-committee: G. Maggetto (VUB), R. Pintelon (VUB), A. Barel (VUB), W. Verhelst (VUB), O. Steenhaut (VUB), Hoffman (RUG)  
Promoter: L. Van Biesen (VUB)

PhD13. **Radar Cross Section Reduction using Multiple - Layer Strip Gratings**  
Gert Van Der Plas  
Judging-committee: G. Maggetto (VUB), R. Van Loon (VUB), A. Van de Capelle (KUL), D. De Zutter (RUG), P. Deligne (UCL)  
Promoters: A. Barel (VUB), E. Schweicher (KMS)

PhD14. **Automated Diagnosis for Arbitrary Digital Circuits**  
Patrick Bakx  
Judging-committee: G. Maggetto (VUB), M. Goossens (VUB), A. Barel (VUB), M. Verlinden (VUB), V. Jonckers (VUB), P. Vandeloo (UIA)  
Promoter: L. Van Biesen (VUB)

PhD15. **Measuring Nonlinear Systems - A Black Box Approach for Instrument Implementation**  
Marc Vanden Bossche  
Judging-committee: G. Maggetto (VUB), R. Pollard (T.U. Leeds), P. Eykhoff (TU Eindhoven), D. De Zutter (RUG), Rik Pintoel (VUB), D. Ritting (Hewlett Packard - USA)  
Promoters: A. Barel (VUB), J. Schoukens (VUB)

PhD16. **Identification of Multi-Input Multi-Output Systems using Frequency-Domain Models**  
Patrick Guillaume  
Doctoral dissertation, Vrije Universiteit Brussel, June, 1992  
Judging-committee: G. Maggetto (VUB), A. Barel (VUB), M. Van Overmeire (VUB), P. Eykhoff (TU Eindhoven), M. Gevers (UCL), J. Vandewalle (KUL)  
Promoters: J. Schoukens (VUB), R. Pintelon (VUB)

Hugo Van hamme  
Doctoral dissertation, Vrije Universiteit Brussel, June, 1992  
Judging-committee: G. Maggetto (VUB), A. Barel (VUB), F. Delbaen (VUB), M. Vanden Bossche (Hewlett Packard Belgium), A. van den Bos (TU Delft), B. De Moor (KUL), L. Ljung (University of Linköping)  
Promoters: R. Pintelon (VUB), J. Schoukens (VUB)

PhD18. **Identification of Linear Systems from Amplitude Information only**  
Yves Rolain  
Judging-committee: G. Maggetto (VUB), A. Barel (VUB), F. Delbaen (VUB), P. Eykhoff (TU Eindhoven), A. van den Bos (TU Delft), K. Godfrey (Univ. of Warwick, UK), J. Vandewalle (KUL)
Promoters: J. Schoukens (VUB), R. Pintelon (VUB)

PhD19. **The Use of the Method of Moments in Designing NMR Antennas**  
Guido Annaert  
Doctoral dissertation, Vrije Universiteit Brussel, December, 1993  
Judging-committee: G. Maggetto (VUB), R. Van Loon (VUB), R. Luypaert (VUB-AZ), R. Turner, C. De Wagter (RUG), P. Van Hecke (AGFA-GEVAERT NV.), M. Lumori (VECO)  
Promoters: A. Barel (VUB), M. Osteaux (VUB-AZ)

Luc Peirlinckx  
Doctoral dissertation, Vrije Universiteit Brussel, June 1994  
Judging-committee: G. Maggetto (VUB), A. Barel (VUB), L. Bjørnø (TU Denmark), P. De Wilde (VUB), H. Leroy (KULAK), J. Van Campenhout (UG), J.P. Sessarego (CNRS-LMA, France)  
Promoters: L. Van Biesen (VUB), J. Schoukens (VUB)

PhD21. **Radar Cross Section Calculations of Three-Dimensional Objects, Modelled by CAD**  
Isabelle De Leeneer  
Judging-committee: G. Maggetto (VUB), V. Stein, D. De Zutter (UG), A. Van De Capelle (KUL), R. Van Loon (VUB)  
Promoters: A. Barel (VUB), E. Schweicher (KMS)

PhD22. **Design and Realization of Low Crest Factor Broadband Microwave Excitation Signals**  
Tom Van den Broeck  
Doctoral Dissertation, Vrije Universiteit Brussel, September 1995  
Judging-committee: G. Maggetto (VUB), J. Tiberghien (VUB), L. Martens (UG), R. Pollard (University of Leeds), M. Vanden Bossche (Hewlett Packard Belgium)  
Promoters: A. Barel (VUB), L. Peirlinckx (VUB)

PhD23. **Accurate Experimental Modelling of Bounded Wave Propagation in Viscoelastic Materials**  
Dayu Zhou  
Doctoral Dissertation, Vrije Universiteit Brussel, October 1995  
Judging-committee: G. Maggetto (VUB), P. Guillaume (VUB), L. Bjørnø (TU Denmark), H. Leroy (KULAK), M. Lumori (VECO), J.P. Sessarego (CNRS-LMA, France), I. Veretennicoff (VUB)  
Promoters: L. Van Biesen (VUB), L. Peirlinckx (VUB)

PhD24. **Calibration of a Measurement System for High Frequency Nonlinear Devices**  
Jan Verspecht  
Doctoral Dissertation, Vrije Universiteit Brussel, November 1995  
Judging-committee: G. Maggetto (VUB), J. Schoukens (VUB), A. Cardon (VUB), M. Vanden Bossche (Hewlett Packard, Belgium), L. Martens (RUG), B. Nauwelaers (KUL), U. Lott, A. Roddie, R. Pintelon (VUB), I. Veretennicoff (VUB)  
Promoter: A. Barel (VUB)

PhD25. **Performance with dielectric resonators at microwave frequencies for studying the pairing state in high-Tc superconductors**  
Andrei Mourachkine  
Judging-committee: W. Van Rensbergen (VUB), G. Van Tendeloo (VUB), J. Drowart (VUB), N. Klein (IFF, Julich), V. Gasumyants (St. Petersburg)  
Promoters: A. Barel (VUB), S. Tavernier (VUB), R. Deltour (ULB)

Gerd Vandersteen  
Doctoral dissertation, Vrije Universiteit Brussel, April 1997  
Judging-committee: G. Maggetto (VUB), A. Barel (VUB), M. Gevers (UCL), L. Ljung (University of Linköping), A. van den Bos (TU Delft), J. Vandewalle (KUL)  
Promoters: R. Pintelon (VUB), J. Schoukens (VUB)

PhD27. **Frequency Domain Identification of Transmission Lines from Time Domain Measurements**  
Patrick Boets  
PhD28. Nonparametric Identification of Nonlinear Mechanical Systems
Stefaan Duym
Promoters: J. Schoukens (VUB), R. Pintelon (VUB)

PhD29. Design of Digital Chebyshev Filters in the Complex Domain
Rudi Vuerinckx
Promoters: J. Schoukens (VUB), Y. Rolain (VUB)

PhD30. Caching in Dataflow-Based Instrumentation & Measurement Environments
Eli Steenput
Doctoral dissertation, Vrije Universiteit Brussel, October 1999
Promoters: J. Schoukens (VUB), Y. Rolain (VUB)

PhD31. Standstill Frequency Response Measurement and Identification Methods for Synchronous Machines
Jef Verbeeck
Promoters: R. Pintelon (VUB), Ph. Lataire (VUB)

PhD32. Nonlinear Identification with Neural Networks and Fuzzy Logic
Jürgen Van Gorp
Doctoral dissertation, Vrije Universiteit Brussel, August 2000
Promoters: J. Schoukens (VUB), R. Pintelon (VUB)

PhD33. Patient and staff dosimetry in diagnostic radiology
Jessica Pages Pulido
Promoter: L. Van Biesen (VUB)

PhD34. Development of New Measuring and Modelling Techniques for RFICs and their Nonlinear Behaviour
Wendy Van Moer

PhD35. High Spatial Resolution Experimental Modal Analysis
Steve Vanlanduit
Promoters: J. Schoukens (VUB), P. Guillaume (VUB)
PhD37. Spectral and Kinetic Analysis of Radiation Induced Optical Attenuation in Silica: Towards Intrinsic Fibre Optic Dosimetry?
Borgermans Paul
Judging-committee: G. Maggetto (VUB), J. Vereecken (VUB), J. Schoukens (VUB), I. Veretennicoff (VUB), B. Neerdael (SCK-CEN), M. Decréton (SCK-CEN), David Griscom (Naval Research Laboratory, USA)
Promoter: Alain Barel (VUB)

PhD38. Multi-Carrier Modulation with Reduced Peak to Average Power Ratio
Zekri Mohamed
Doctoral Dissertation, Vrije Universiteit Brussel, February 2002
Judging-committee: G. Maggetto (VUB), J. Vereecken (VUB), A. Barel (VUB), J. Tiberghien (VUB), P. Boets (VUB), G. Vanhoutte (Belgacom), S. Popescu (Polytechnic Univ. of Bucharest)
Promoter: L. Van Biesen

PhD39. Parametric modeling and estimation of ultrasonic bounded beam propagation in viscoelastic media
Bey Temsamani Abdellatif
Doctoral Dissertation, Vrije Universiteit Brussel, February 2002
Judging-committee: G. Maggetto (VUB), J. Vereecken (VUB), A. Barel (VUB), D. Van Hemelrijck (VUB), L. Peirlinckx (Phonetic-Topographics, Ieper), O. Leroy (KULAK), Leif Bjørnø (Technical University of Denmark, Lyngby (DK)), Jean-Pierre Sessarego (Laboratoire d'Acoustique et de Mecanique, CNRS, Marseille (F))
Promoter: L. Van Biesen

PhD40. Measurement and modelling of the noise behaviour of high-frequency nonlinear active systems
Geens Alain
Doctoral Dissertation, Vrije Universiteit Brussel, May 2002
Judging-committee: G. Maggetto (VUB), J. Vereecken (VUB), R. Pintelon (VUB), R. Pollard (University of Leeds, UK), D. Van Hoenacker (UCL), J.C. Pedro (Universidade de Aveiro, Portugal), A. Barel (VUB)
Promoter: Y. Rolain

PhD41. Model Based Calibration of D/A Converters
Vargha Balázs
Doctoral Dissertation, Vrije Universiteit Brussel, June 2002
Judging-committee: G. Maggetto (VUB), J. Vereecken (VUB), A. Barel (VUB), B. Bell (NIST, USA), I. Kollar (TUB, Hungary), Y. Rolain (VUB), G. Vandersteen (VUB-IMEC)
Promoters: Johan Schoukens, István Zoltán (TUB)

PhD42. Frequency Response Function Measurements in the Presence of Non-Linear Distortions
Kenneth Vanhoeacker
Doctoral Dissertation, Vrije Universiteit Brussel, June 2003
Judging-committee: G. Maggetto (VUB), J. Vereecken (VUB), A. Barel (VUB), P. Guillaume (VUB), H. Sol (VUB), J. Swevers (KUL), H. Van der Auweraer (LMS International)
Promoter: Johan Schoukens

PhD43. Identification of Nonlinear Systems using Interpolated Volterra Models
József G. Németh
Doctoral Dissertation, Vrije Universiteit Brussel, June 2003
Judging-committee: A. Barel (VUB), T. Dobrowiecki (Budapest University of Technology and Economics), M.P. Kennedy (University College Cork), R. Pintelon (VUB)
Promoters: Johan Schoukens, István Kollár (TUB)

PhD44. Identification of block-oriented nonlinear models
Philippe Crama
Doctoral Dissertation, Vrije Universiteit Brussel, June 2004
Judging-committee: G. Maggetto (VUB), J. Vereecken (VUB), P. Guillaume (VUB), L. Ljung (Linköping University, Sweden), M. Verhaegen (TUD, The Netherlands), J. Vandewalle (KUL), A. Barel (VUB), R. Pintelon(VUB)
Promoters: Johan Schoukens, Y. Rolain

PhD45. Identification of the Time Base in Environmental Archives
Fjo De Ridder
PhD46. **Optimisatie van patiënt dosissen, gekoppeld aan beeldkwaliteit, in de vasculaire radiologie**

Lara Struelsen

Doctoral Dissertation, Vrije Universiteit Brussel, January 2005

Judging-committee: Promoter: R. Van Loon, co-promotors: H. Bosmans (KUL), F. Vanhavere (SCK-CEN)

PhD47. **Modelling, Designing and Developing a Multidisciplinary Geodatabase GIS with the Implementation of RDBMS in conjunction with CAD and different GIS applications for the development of Coastal/Marine Environment**

Tesfazghi Ghebre Egziabeher

Doctoral Dissertation, Vrije Universiteit Brussel, September 2005

Judging-committee: E. Vandijck (VUB), F. Canters (VUB), A. Barel (VUB), S. Wartel (Royal Belgian Institute of Natural Sciences), L. Peirlinckx (Phonetics Topographics, Belgium)

Promoters: L. Van Biesen and Marc Van Molle (Geography dept., fac. of Sciences)

PhD48. **Modeling of Substrate Noise Impact on CMOS VCOS on a Lightly-Doped Substrate**

Charlotte Soens


PhD49. **Evaluation of deep-sub-quarter micron CMOS technology: low noise amplifiers, oscillators and ESD reliability**

Dimitri Linten


Promoters: Y. Rolain, P. Wambacq and M. Kuijk

Judging-committee: G. Maggetto, J. Vereecken, A. Barel, M.I. Natarajan (Mentor IMEC), I. Smedes (Philips Semiconductors), M. Tiebout (Infineon)

PhD50. **Verification and Correction of Test Signals with a Spectrum Analyzer**

Daan Rabijns

Doctoral Dissertation, Vrije Universiteit Brussel, March 2006

Promoters: G. Vandersteen, J. Schoukens

Judging-committee: P. Lataire, J. Vereecken, I. Kollar (Budapest Univ. of Techn. & Economics), D. DeGroot (CCNi Measurement Service), P. Guillaume, W. Van Moer

PhD51. **Impact and Mitigation of Analog Impairments in Multiple Antenna Wireless Communications**

Jian Liu


Promoters: A. Barel, J. Stiens, G. Vandersteen

Judging-committee: P. Lataire, J. Vereecken, L. Van der Perre (IMEC), V. Öwall (Lund University, Sweden), W. Van Moer

PhD52. **Development and evaluation of a numerical method for the identification of a physical system described by a partial differential equation: a case study**

Kathleen De Belder


Promoters: R. Pintelon, J. Schoukens

Judging-committee: Ph. Lataire, J. Vereecken, J. Swevers (KUL), P. Guillaume, H. Van der Auweraer (LMS International), H. Sol, P. Roose (Cytec)

PhD53. **Contributions to Large-Signal Network Analysis**

Frans Verbeyst


Promoter: Y. Rolain

Judging-committee: J. De Ruyck, Jean Vereecken, Alain Barel, Don DeGroot (CCNi Measurement Services, Andrews University, Michigan, USA), Rik Pintelon, Roger Pollard (University of Leeds, UK), Johan Schoukens, Steve Vnlanduit
PhD54. **Contribution to severe weather and multimodel ensemble forecasting in Belgium**

David Dehenauw

Doctoral Dissertation, Vrije Universiteit Brussel, November 2006

Promoters: A. Barel, H. Declerik


PhD55. **A system identification view on two aquatic topics: phytoplankton dynamics and water mass mixing**

Anouk de Brauwere


Promoters: Willy Baeyens, Johan Schoukens

Judging-committee: Robert Finsey, Frank Dehairs, Rik Pintelon, An Smeyers-Verbeke, Joos Vandewalle (KUL), Eric Deleersnijder (UCL), Karline Soetaert (NIOO-KNAW), Johannes Karstensen (University of Kiel)

PhD56. **Ultra-Wideband transceiver for low-power low data rate applications**

Julien Ryckaert


Promoters: Yves Rolain, Piet Wambacq (IMEC)

Judging-committee: Annick Hubin, Rik Pintelon, Gerd Vandersteen, J. Rabaey (University of Berkeley, USA), M. Tiebout (Inffineon Germany), Christof Debaes, C. Desset (IMEC)

PhD57. **Measuring, modeling and realization of high-frequency amplifiers**

Ludwig De Locht


Promoters: Yves Rolain, Gerd Vandersteen

Judging-committee: Annick Hubin, Rik Pintelon, Wendy Van Moer, Danielle VAnhoenacker (UCL), Andrea Ferrero (Politecnico di Torino), Christof Debaes (VUB), Marc Vanden Bossche (NMDG Engineering)

PhD58. **Body Area Communications: Channel characterization and ultra-wideband system-level approach for low power**

Andrew Fort


Promoters: Leo Van Biesen, Piet Wambacq (IMEC)

Judging-committee: Annick Hubin, Rik Pintelon, G. Vandersteen, Y. Hao (Univ. of London), C. Desset (IMEC)

PhD59. **Algorithms for identifying guaranteed stable and passive models from noisy data**

Tom D’Haene


Promoter: Rik Pintelon

Judging-committee: Gert Desmet, Jean Vereecken, Patrick Guillaume, Paul Van Dooren (UCL), Tom Dhaene (UGent), Martine Olivi (INRIA), Gerd Vandersteen

PhD60. **Identification of Nonlinear Systems Using Polynomial Nonlinear State Space Models**

Johan Paduart


Promoters: Johan Schoukens, Rik Pintelon

Judging-committee: Annick Hubin, Jean Vereecken, Steve Vanlanduit, Lennart Ljung (Linköping University), Jan Swevers (KUL), Yves Rolain

PhD61. **GSM-based Positioning: Techniques and Application**

Nico Deblauwe

Doctoral Dissertation, Vrije Universiteit Brussel, June 2008

Promoters: Leo Van Biesen, Prof. Dr. Claudia Linthoff-Popien (Ludwig-Maximilians-Univ. Munchen)

Judging-committee: Dirk Lefeber, Rik Pintelon, Peter Schelkens, Wendy Van Moer, Luc Vandendorpe (Université Catholique de Louvain), Luc Martens (Universiteit Gent), Fredrik Gustafsson (Linköping University)


Anna Marconato

Doctoral Dissertation, Vrije Universiteit Brussel - Università degli Studi di Trento, March 2009

Promoters: Prof. Dario Petri, Johan Schoukens, Bruno Caprile

Judging-committee: Annick Hubin, Gerd Vandersteen, Michel Verleysen (UCL), Davide Anguita (University of Genova), Anne Nowé
PhD63. **A framework for the analysis and modelling of substrate noise**  
Stephane Bronckers  
Doctoral Dissertation, Vrije Universiteit Brussel, June 2009  
Promoters: G. Van der Plas, G. Vandersteen  
Judging-committee: A. Hubin, voorzitter, R. Pintelon, P. Wambacq, M. Nagat, (Kobe University, Japan), F.J. Clément, (Coupling Wave Solutions, France), W. Schoenmaker (Magwel, Belgium)

PhD64. **Identification and use of nonparametric noise models extracted from overlapping subrecords**  
Kurt Barbé  
Doctoral Dissertation, Vrije Universiteit Brussel, September 2009  
Promoters: Rik Pintelon, Johan Schoukens  
Judging-committee: Annick Hubin, Patrick Guillaume, Gerd Vandersteen, Lennart Ljung (Linköping University), Jérôme Antoni (Univ. de Technologie de Complègne), Joos Vandewalle (KULeuven), Steve Vanlanduit

PhD65. **Model Fitting in Frequency Domain Imposing Stability of the Model**  
László Balogh  
Doctoral Dissertation, Vrije Universiteit Brussel, October 2009  
Promoters: Rik Pintelon, István Kollár (TUBudapest)  
Judging-committee: Johan Schoukens, Patrick Guillaume, Joos Vandewalle (KULeuven), Steve Vanlanduit, Barnabás Garay (TUBudapest)

PhD66. **CMOS building blocks for 60 GHz Phased-Array receivers**  
Karen Scheir  
Promoters: Piet Wambacq, Yves Rolain  
Judging-committee: A. Hubin, R. Pintelon, G. Vandersteen, J. Long (TUDelft, Nederland), K. Halonen (Helsinki University of Technology, Finland), C. Debaes

PhD67. **Localization in wireless networks and co-existence of broadband services**  
Mussa Bshara  
Doctoral Dissertation, Vrije Universiteit Brussel, June 2010  
Promoter: Leo Van Biesen  
Judging-committee: J. Tiberghien, R. Pintelon, P. Schelkens (IBBT), F. Gustafsson (Linkoping Universitet), G. Vandersteen, P. Boets (Alcatel-Lucent-bell), L. Vandendorpe (UCL)

PhD68. **Advanced calibration and Instrumentation setups for nonlinear RF devices**  
Liesbeth Gommé  
Doctoral Dissertation, Vrije Universiteit Brussel, August 2010  
Promoter: Yves Rolain  
Judging-committee: A. Hubin, R. Pintelon, G. Vandersteen, K. Godfrey (University of Warwick), D. Barataud (University of Limoges), M. Vanden Bossche (NMDG Engineering)

PhD69. **A Bayesian Model To Construct A Knowledge Based Spatial Decision Support System For The Chaguana River Basin**  
Indira Nolivos Alvarez  
Doctoral Dissertation, Vrije Universiteit Brussel, October 2010  
Promoters: Leo Van Biesen, Pilar Cornejo (ESPOL, Ecuador)  
Judging-committee: J. Tiberghien, R. Pintelon, W. Bauwens, Pedro Girao (Universidade Técnica de Lisboa), Rony Swennen (KUL), Ann Nowé

PhD70. **Best Linearized models for RF systems**  
Koen Vandermot  
Doctoral Dissertation, Vrije Universiteit Brussel, October 2010  
Promoter: Yves Rolain  
Judging-committee: W. Bauwens, R. Pintelon, G. Vandersteen, D. Vanhøenacker (UCL), T. Dhaene (Universiteit Gent), M. Vanden Bossche (NMDG Engineering)
4.10 THESIS TOT HET BEHALEN VAN HET AGGREGAAT VAN HET HOGER ONDERWIJS

1. System Identification. A Frequency Domain Modeling Approach
   Johan Schoukens
   Geaggregeerde van het hoger onderwijs, Vrije Universiteit Brussel, 1991
   Judging-committee: G. Maggetto (VUB), G. Baron (VUB), G. Vansteenkiste (VUB), P. Eykhoff (TU Eindhoven), A. van den Bos (TU Delft), J. Vandewalle (KUL), M. Gevers (UCL)
   Promoters: J. Renneboog (VUB), A. Barel (VUB)

2. Frequency Domain Identification of Linear Time Invariant Systems
   Rik Pintelon
   Geaggregeerde van het hoger onderwijs, Vrije Universiteit Brussel, 1994
   Judging-committee: G. Maggetto (VUB), A. Cardon (VUB), G. Baron (VUB), P. Eykhoff (TU Eindhoven), M. Gevers (UCL), A. van den Bos (TU Delft), J. Vandewalle (KUL), G. Van Steenkiste (RUG)
   Promoter: A. Barel (VUB)
5. Location of the university (VUB) and the dept. ELEC

Getting to the department ELEC of the “Vrije Universiteit Brussel”

5.1 ARRIVAL BY CAR:

Take the “Ring” and exit at the crossing with the motorway E411 direction centre of Brussels. At the end of the motorway, take the viaduct (go straight on), and at the second traffic lights, turn on right (“Triomflaan”), the VUB is situated on the left side of this road, starting from entrance 6 (see next map).

5.2 FROM THE BRUSSELS NATIONAL AIRPORT AT ZAVENTEM:

Brussels International Airport is at Zaventem, 14 km from the city centre.

- Information can be obtained by phone: Tel +32 2 753 42 21 / +32 2 723 31 11
- Flight information: Tel +32 900 70 000 (7 a.m. - 10 p.m.)
- www.brusselsairport.be

From the airport, every 20 minutes the rail shuttle quickly takes you to the North Station in the centre of Brussels. At the North Station (“Bruxelles Nord”), you take the train to Etterbeek (direction Etterbeek or Louvain La Neuve) and get off the train in Etterbeek, which is 10 min.
walking distance from the VUB. You only pay € 3.90 for a first class ticket, and € 2.50 for a second class ticket (a taxi or cab from airport to the University is about € 50.00).

More information and timetables of the Belgian railways: www.b-rail

5.3 FROM BRUSSELS SOUTH AIRPORT (CHARLEROI)

Situated to the south of Brussels, approximately 60 km away, Brussels-South Charleroi airport mainly houses low-cost airlines. www.charleroi-airport.com

A bus links Charleroi Brussels-South and the Gare du Midi railway station in Brussels more than 20 times a day.

The timetables are organised to coincide with Ryanair airline flights.

- Brussels to Charleroi: The shuttle departure point is situated at the junction of rue de France and rue de l'Instruction (follow "Thalys" exit at the Gare du Midi station).
- Charleroi to Brussels: shuttle departs 30 minutes after the Ryanair airline flight arrives at the airport. One-way ticket fare: 10.00 € (tickets are sold inside the shuttle)

5.4 ARRIVAL BY TRAIN:

Change in “Bruxelles Nord“ and take the train to Etterbeek (direction Etterbeek or Louvain La Neuve)

www.b-rail.be
5.5 ARRIVAL BY SUBWAY (€ 1.80/JUMP-TICKET):

Take line 5 direction "Hermann-Debroux" and get off at "Petillon", which is also 10 min. walking distance from the VUB.

More information about Brussels subway: www.stib.be

The dept. ELEC is located in building K, 6th floor.