Application

2015-03-31

2015-05494	Enqvist, Martin	NT-14

Information about applicant

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Project site: Institutionen för systemteknik (ISY)

Information about application

Call name: Forskningsbidrag Stora utlysningen 2015 (Naturvetenskap och teknikvetenskap)

Type of grant: Projektbidrag

Focus: Fri

Subject area:

Project title (english): System identification in nonlinear feedback networks

Project start: 2016-01-01

Project end: 2019-12-31

Review panel applied for: NT-14

Classification code: 20202. Reglerteknik

Keywords: system identification, network, nonlinear system, feedback

Funds applied for

Year:	2016	2017	2018	2019
Amount:	944,000	944,000	944,000	944,000

Descriptive data

Project info

Project title (Swedish)*

Systemidentifiering i olinjära återkopplade nätverk

Project title (English)*

System identification in nonlinear feedback networks

Abstract (English)*

This project concerns data-based modeling of subsystems in nonlinear feedback networks using a statistical system identification framework. Since feedback is a fundamental principle both in nature and in engineering and since many systems exhibit nonlinear behaviors, examples of such modeling problems can be found in various areas, e.g., process control, communication systems, aerospace, robotics, and system biology. The focus is here on methods that are reliable also when the information about the disturbance distribution is incomplete or too complicated to be useful in the estimation method.

The unique feature of this project is that it will extend the existing methods for identification in linear dynamical networks to modeling problems in nonlinear networks with mild assumptions the disturbance signals that are present in the network. The fundamental challenges with this setup will be analyzed theoretically, and methods for detection of some of the relevant features will be developed. Furthermore, the particular subproblem of reliable estimation of a linear model in a nonlinear feedback network will be addressed as well as estimation of nonlinear structured models in feedback networks. Some practical aspects of nonlinear feedback networks will be investigated and evaluated experimentally using electromechanical lab systems. Since there seems to be an growing general interest for estimation problems concerning networks and since there are many relevant application areas, this project contains a number of highly relevant research problems.

Popular scientific description (Swedish)*

Eftersom återkoppling är en grundläggande princip både i naturen och inom ingenjörsvetenskapen finns det gott om tillämpningar som kan beskrivas med hjälp av nätverk, till exempel inom processreglering, robotik, kommunikationssystem och systembiologi. Många av dessa nätverk innehåller olinjära komponenter och påverkas både av signaler som vi är intresserade av och av slumpmässiga störningar och eftersom nätverken kan vara mycket stora och ha komplicerade strukturer kan det vara svårt att ta fram och upprätthålla noggranna beskrivningar av deras egenskaper.

Ett sätt att få kunskap om en intressant del av ett nätverk är att skatta en modell av den baserat på mätningar av vissa signaler som finns i nätverket. Det här projektet handlar om just denna klass av modellskattningsproblem och syftet är här att öka förståelsen för de utmaningar som finns i det här sammanhanget samt att utveckla nya och förbättrade skattningsmetoder. Eftersom det verkar finnas ett växande intresse för olika typer av skattningsproblem som rör nätverk och eftersom det finns gott om tillämpningar för sådana metoder är det här ett projekt som innehåller ett antal mycket relevanta forskningsproblem.

Project period

Number of project years*

4

Calculated project time*

2016-01-01 - 2019-12-31

Classifications

Select a minimum of one and a maximum of three SCB-codes in order of priority.

Select the SCB-code in three levels and then click the lower plus-button to save your selection.

SCB-codes* 2. Teknik > 202. Elektroteknik och elektronik > 20202. Reglerteknik

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Enter a minimum of three, and up to five, short keywords that describe your project.

Keyword 1*

system identification

Keyword 2*

network

Keyword 3*

nonlinear system

Keyword 4

feedback

Keyword 5

Ethical considerations

Specify any ethical issues that the project (or equivalent) raises, and describe how they will be addressed in your research. Also indicate the specific considerations that might be relevant to your application.

Reporting of ethical considerations*

There are no ethical aspects that need to be considered in this project.

The project includes handling of personal data

No

The project includes animal experiments

No

Account of experiments on humans

No

Research plan

System identification in nonlinear feedback networks

Purpose and aims

The main objective of this research project is to develop reliable methods for system identification that can be applied when the investigated system is part of a nonlinear feedback network. Such methods would be very useful in applications where the goal is to estimate a model of a particular subsystem that operates in a complex environment with feedback mechanisms and significant disturbances. Since feedback is a fundamental principle both in nature and in engineering and since many systems exhibit nonlinear behaviors, examples of such modeling problems can be found in various areas, e.g., process control, communication systems, aerospace, robotics, and system biology.

There can be many reasons for limiting the modeling efforts to a particular subsystem rather than to aim for a model of the complete system that is investigated. In many cases, the complexity of the complete system and the corresponding efforts required to obtain a complete model motivates a more restricted approach. For example, this is true in many process control applications where a production plant can contain thousands of control loops with system properties that vary over time. This time-variability makes it necessary to frequently retune some of the controllers, which can be a formidable task and a cause for production inefficiencies. Furthermore, it is common that either the physical systems in the production plant or the process control system, or both, contain nonlinearities and that there are large disturbances in the system with mainly unknown properties. In this application, it would be very convenient to have a reliable method for direct estimation of a model of a particular subsystem from normal production data.

The main challenge with system identification in closed-loop settings is that there is a dependency between the input and output not just through the system that is to be modeled but also through the feedback mechanism. This can complicate the model estimation significantly if there are disturbances in the system, which, to some extent, is always the case in real applications. In particular, this becomes a serious problem when there are nonlinearities somewhere in the feedback loop, and the question how to estimate a particular subsystem in this case is still an open problem. This is the main problem that will be addressed in this project.

Furthermore, the focus here is on general feedback networks that typically contain more than one physical feedback loop and where there can be many external inputs and measurable outputs. The network setting provides some new possibilities compared to the more simple case of one single feedback loop, but also a number of challenges. For example, the availability of more inputs and outputs can be an advantage. On the other hand, it is much harder to obtain an accurate description of all feedback mechanisms that are relevant for the identification of a particular subsystem when there are several feedback paths in the network. As a consequence, it will be much harder to characterize the influence of disturbances in the network case. Hence, this project aims at developing methods that are reliable also when the information about the disturbance spectrum and distribution is lacking or incomplete.

More specifically, this project has the following three aims:

- **Analysis of the nonlinear feedback network subsystem identification problem:** To develop a framework that describes the most relevant features of the problem of estimation of a subsystem in a nonlinear feedback network. Furthermore, methods for detection of some of these features will be investigated with the goal of providing the user with a decision support tool that can be used to distinguish easier problems, which can be handled with the state-of-the-art methods of today, from more challenging problems.

- **Reliable estimation of linear models in nonlinear feedback networks:** To develop new methods that overcome some of the limitations with the existing methods for direct identification of linear systems that operate under nonlinear feedback.

- **Reliable estimation of nonlinear structured models in feedback networks:** To develop methods for identification of subsystems consisting of cascaded blocks of linear subsystems and static nonlinear functions or polynomial subsystems that operate under closed-loop conditions.

Survey of the field

System identification deals with the problem of how to estimate a mathematical model of a dynamical system from measurements of its input and output signals [27]. This is a highly relevant problem within the control field where most modern control design methods are model-based and the modeling of an unknown system can consume a large part of the budget in an industrial control design project. For example, modeling costs between 50% and 75% of the total resources have been reported as typical in advanced control projects [7, 18, 29]. Hence, new methods that can simplify the modeling process have a great potential.

In all realistic cases, an estimated model will only be an approximation of the true system, and the model errors will depend on several factors. Obviously, they will depend on the model structure used, but also on the input signal, the cost function and the process and measurement noises, etc. There is an extensive literature on how these factors affect an estimated model in the special case when both the model and the true system are linear [see, for example, 27, 32]. Some options, such as the choice of model structure and cost function, can be decided offline, after the dataset has been collected, whereas the actual experimental conditions obviously have to be chosen before the identification experiment is carried out. One important experimental condition is whether the input and output data are collected in open or closed loop, i.e., without or with a feedback mechanism that governs the input signal in the experiment.

Estimating a model of system under closed-loop conditions is a necessity in many applications and can be advantageous but also challenging [13, 14, 16]. Closed-loop system identification is a classic topic within the system identification community [15] and many methods exist for direct [1, 2, 3, 4, 11, 19, 28, 29, 35, 45, 46], indirect [41], and joint input-output closed-loop system identification [12, 17, 21, 29, 39, 42]. Most of these methods concern linear systems with linear feedback mechanisms, but there are some results about identification of linear systems with nonlinear feedback [11, 12, 29] or nonlinear closed-loop systems [20, 26, 43]. However, the existing methods for closed-loop identification of nonlinear systems are typically dependent on high signal-to-noise ratios or very particular assumptions about the true system.

Furthermore, the consistency of the estimator used in the most popular of the approaches for identification of linear systems with nonlinear feedback, the prediction-error method applied in a direct fashion, is typically dependent on the invertibility of the complete noise process in the system, i.e., on the fact that a sequence of independent identically distributed variables can be obtained by passing the complete noise process through a stable and causal linear time-invariant filter. This property is difficult to test in practice, but critical for the reliability of the direct prediction-error approaches to closed-loop system identification.

The projection method by Forssell and Ljung [12] is an interesting alternative to the direct prediction-error method that defines a consistent estimator for the linear system dynamics also when there is nonlinear feedback and under weaker assumptions on the complete noise process. This method can be viewed as an generalized version of the two-stage method by Van den Hof and Schrama [39] and involves a first step in which a linear approximate model of the closed-loop system from reference signal to input signal is estimated. Since this closed-loop system is nonlinear due to the nonlinear feedback mechanism, this is one example where a linear model of a nonlinear system turns out to be useful as an initial step in an identification method.

Linear models of nonlinear systems have received much interest during the last decade. The most intuitive method for obtaining such a model is probably differentiation. For example, this approach is used in [31]. Linear approximations of nonlinear systems can be studied also in a stochastic framework [8, 10, 32, 33, 34, 37, 38]. One result that concerns the projection method by Forssell and Ljung [12] is that it is sufficient to estimate a causal linear approximation from reference to input signal if the reference signal is designed in a particular way [8].

Approximate modeling is a topic that has been studied also in the statistical literature. In particular, the results about projection methods for nonlinear regression problems seem to be possible to use also for more general identification problems [5, 24, 25]. In particular, the use of importance weighting [5] is interesting also for general nonlinear approximate identification problems. This is described in [9], where also an application to a Hammerstein identification problem is described.

Finally, there seems to be a growing interest for identification in dynamic networks within the system identification community at the moment. However, the available results are mainly concerned with identification in linear network structures [6, 30, 36, 40] or by network structure reconstruction in nonlinear networks using linear approximate models [44]. Hence, the present project proposal provides a novel generalization of the present state-of-the-art results.

Project description

Theory

The main objective of this research project is to develop methods for estimation of models of subsystems that are part of nonlinear feedback networks. The analysis of this problem will be made using a statistical framework and properties such as consistency, unbiasedness, and asymptotic efficiency will be investigated for the developed estimators. There will be a particular focus on methods that can be used with realistically mild assumptions on the system noise properties and that can be shown to produce reliable estimates under many different experimental conditions. The fact that the interesting subsystems are supposed to be parts of rather complex nonlinear feedback network structures is one of the motivating factors for avoiding methods that rely on very specific assumptions, since such assumptions are hard to evaluate in this context.

Both general theoretical problems concerning estimation of subsystems in nonlinear feedback networks and some application-specific questions that concern practical implementation and usage of the developed methods will be studied in this project.

I. Analysis of the nonlinear feedback network subsystem identification problem

A starting point in this project will be to formulate a few benchmark problems that concern estimation of subsystems in nonlinear feedback networks. Ideally, these benchmark problems should be able to illustrate some of the challenges that come with this problem and some of the limitations for the state-of-the-art methods of today. Working with benchmark problems like this has been a popular theme at a number of recent system identification conferences and has a potential to increase the interest for this problem within the relevant research community.

In parallel to the formulation of benchmark problems, the features of the nonlinear network estimation problems will be analyzed theoretically, hopefully leading to a deeper understanding. This theoretical analysis will also be used as a driver for the development of detectors that can alert a practical user that a particular estimation problem exhibits some features that require special care. Such detectors will be highly useful in applications such as process industry, where a single engineer might have to assess the quality of thousands of models on a more or less daily basis.

Some questions that will be studied in this project are:

- How complex noise distributions are required for the direct prediction-error approach to closed-loop identification to give an inconsistent subsystem estimator?

- Assume that a particular subsystem has one input and one output signal, but that there are more inputs and outputs available in the network. How can the value of using these additional signals in the identification method be assessed?
- How should properties of the system noise be evaluated in practice? Can the model residuals be used for this purpose?
- How can knowledge about a part of the feedback network be used in an efficient way to improve the model estimates?

II. Reliable estimation of linear models in nonlinear feedback networks
It seems that methods like the projection method by Forssell and Ljung [12] have some advantages over the direct prediction-error method [11] when the system noise is noninvertible. One way to facilitate the use of this projection method is to use special external excitation signals in the identification experiment. Here, the focus will be on other ways to improve and robustify this and related methods for estimation of linear models in nonlinear feedback networks.

An interesting feature of this problem formulation is that it can be useful in more general settings than might be expected at first. For example, it is possible to obtain estimation problems that belong to this category by introducing particular sensors at suitable positions in certain complex mechanical structures. Using these sensor signals, it is sometimes possible to formulate a linear system identification problem with nonlinear feedback in such a way that an estimated model will reveal an interesting feature of the overall system that would have been much harder to estimate using a complete modeling approach. However, such artificial network formulations might exhibit features that are uncommon in real, physical networks, e.g., algebraic loops and improper transfer functions in continuous time. These features will be interesting to investigate in more detail.

Some questions that will be studied in this project are:

- Which approximate nonlinear model structures of the closed-loop system between reference and input signal are suitable to use in two-stage or projection methods for joint input-output system identification?
- Can the variance properties of the estimator be improved by using some kind of iterative approach, for example, if the nonlinear feedback mechanism is known?
- How should the reference signal be designed in order to improve the performance of the two-stage or projection method?
- Can importance weighting be used to improve the convergence rate of some closed-loop estimators?
- How can nonstandard features such as algebraic loops and improper transfer functions be handled?

III. Reliable estimation of nonlinear structured models in feedback networks
Open-loop identification of block-oriented and polynomial systems are well-studied problems within the system identification community. Here, the focus will be on estimation of models with these structures under closed-loop conditions.

Some questions that will be studied in this project are:

- Can the two-stage and projection methods be extended to handle also block-oriented and polynomial systems?
- Can some closed-loop estimation problems concerning single input single output block-oriented systems be reformulated as closed-loop multiple input single output linear identification problems?

- Can the statistical methods for dimension reduction be used to simplify some of the estimation problems concerning nonlinear feedback networks?
- Which model structures are suitable for closed-loop identification of block-oriented or polynomial systems? Can nonparametric models be advantageous in this setting?
- How should the polynomial implicit models that appear in some approaches to reinforcement learning be estimated in order to mitigate the effects of feedback and noise?
- Which excitation signals are suitable for adaptive control or reinforcement learning when the true system has a block-oriented or polynomial structure?

Methodology

The standard methodology for research in system identification and data-based modeling will be used here and the research topics will be addressed either from practical or theoretical points of view. When attacking the problems from their practical side, real-life datasets will first be collected in identification experiments with lab processes using computerized measurement systems. Furthermore, control engineers active in industry will be contacted for practical tests of the developed methods.

However, the main focus in this project will be on theoretical investigations of the research problems outlined above. Initially, the focus will be on formulating a detailed enough description of the problem of estimating a subsystem in a nonlinear feedback network. Later, novel methods for estimation of models with particular structures will be developed.

Approaches for adaptive control and reinforcement learning often result in estimation problems where some kind of implicit or explicit model should be estimated from data that have been collected under nonlinear feedback. Hence, these approaches will be used to motivate the research problems studied in this project. Furthermore, adaptive control and reinforcement learning will also be used to define application examples for the developed methods.

Besides studies of real-life data and theoretical analyses, computer simulations will be used when investigating many of the research problems.

Time plan

The plan is to start this project on January 1st, 2016 and finish it on December 31st, 2019.

Implementation

The main focus within the field of system identification is on design and analysis of methods for data-based modeling. Hence, most results are in the form of algorithms that easily can be implemented in modern computer systems. The results obtained in the proposed project will be no exception and they will be implemented in test software.

Participating researchers

The main research in this project will be done by a PhD student under the supervision and assistance of the main applicant.

Significance

Data-based modeling of subsystems in nonlinear feedback networks is a topic that is relevant for several research areas, and the proposed project has thus a high relevance. The emphasis on reliability and weak assumptions on the experimental conditions is also a unique project feature that puts the focus on fundamental theoretical results with a high practical relevance.

Preliminary results

Some preliminary, and so far unpublished, results concerning the inconsistency of the direct prediction-error method in some closed-loop identification settings where there is a nonlinear feedback mechanism have already been obtained. Furthermore, some results concerning closed-loop identification of nonlinear and unstable aircraft systems can be found in [23] and in the thesis [22], which has been written under the supervision of the main applicant.

International and national collaboration

The plan is to invite Prof. Johan Schoukens and Prof. Rik Pintelon and co-workers at Vrije Universiteit Brussel in Belgium for cooperation within this project, in particular concerning methods for obtaining approximate nonlinear models. Furthermore, there are strong links between the research groups for Automatic Control at Linköping University and KTH in Stockholm and the plan is to invite also Prof. Håkan Hjalmarsson and Prof. Bo Wahlberg at KTH for cooperation on some subproblems of common interest.

References

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Interdisciplinarity

My application is interdisciplinary

☐

An interdisciplinary research project is defined in this call for proposals as a project that can not be completed without knowledge, methods, terminology, data and researchers from more than one of the Swedish Research Councils subject areas; Medicine and health, Natural and engineering sciences, Humanities and social sciences and Educational sciences. If your research project is interdisciplinary according to this definition, you indicate and explain this here.

Click here for more information

Scientific report

Scientific report/Account for scientific activities of previous project

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Budget and research resources

Project staff

Describe the staff that will be working in the project and the salary that is applied for in the project budget. Enter the full amount, not in thousands SEK.

Participating researchers that accept an invitation to participate in the application will be displayed automatically under Dedicated time for this project. Note that it will take a few minutes before the information is updated, and that it might be necessary for the project leader to close and reopen the form.

Dedicated time for this project

	Role in the project	Name	Percent of full time
1	Applicant	Martin Enqvist	20
2	PhD Student		80

Salaries including social fees

	Role in the project	Name	Percent of salary	2016	2017	2018	2019	Total
1	Applicant	Martin Enqvist	20	200,000	200,000	200,000	200,000	800,000
2	Other personnel without doctoral degree	PhD student	80	440,000	440,000	440,000	440,000	1,760,000
	Total			640,000	640,000	640,000	640,000	2,560,000

Other costs

Describe the other project costs for which you apply from the Swedish Research Council. Enter the full amount, not in thousands SEK.

Premises

Type of premises	2016	2017	2018	2019

Running Costs

	Running Cost	Description	2016	2017	2018	2019	Total
1	Conferences	Fees and travels	60,000	60,000	60,000	60,000	240,000
2	Equipment	Computers and software	20,000	20,000	20,000	20,000	80,000
	Total		80,000	80,000	80,000	80,000	320,000

Depreciation costs

Depreciation cost	Description	2016	2017	2018	2019

Total project cost

Below you can see a summary of the costs in your budget, which are the costs that you apply for from the Swedish Research Council. Indirect costs are entered separately into the table.

Under Other costs you can enter which costs, aside from the ones you apply for from the Swedish Research Council, that the project includes. Add the full amounts, not in thousands of SEK.

The subtotal plus indirect costs are the total per year that you apply for.

Total budget

Specified costs	2016	2017	2018	2019	Total, applied	Other costs	Total cost
Salaries including social fees	640,000	640,000	640,000	640,000	2,560,000		2,560,000
Running costs	80,000	80,000	80,000	80,000	320,000		320,000
Depreciation costs					0		0
Premises					0		0
Subtotal	720,000	720,000	720,000	720,000	2,880,000	0	2,880,000
Indirect costs	224,000	224,000	224,000	224,000	896,000		896,000
Total project cost	944,000	944,000	944,000	944,000	3,776,000	0	3,776,000

Explanation of the proposed budget

Briefly justify each proposed cost in the stated budget.

Explanation of the proposed budget*

The project budget consists mainly of salaries. The plan is that a PhD student will work 80% of his/her time on the project and that Martin Enqvist will provide 20% of his time for the supervision of this PhD student and for selected subproblems. The annual salary costs are 440000 SEK and 200000 SEK, respectively. Using the standard model for overhead costs (35%) this corresponds to 224000 SEK in indirect costs each year. Furthermore, there will be a need for travels and conference fees of 60000 SEK per year and computer equipment of 20000 SEK per year.

Other funding

Describe your other project funding for the project period (applied for or granted) aside from that which you apply for from the Swedish Research Council. Write the whole sum, not thousands of SEK.

Other funding for this project

Funder	Applicant/project leader	Type of grant	Reg no or equiv.	2016	2017	2018	2019

CV and publications

CV

Curriculum Vitae

1. Higher education qualification

Master of Science (Swedish: Civilingenjör) in Applied Physics and Electrical Engineering, Linköping University, Sweden. Branch of studies: Applied Mathematics. December 2000.

2. Doctoral degree

Doctor of Philosophy (Swedish: Teknologie doktor) in Automatic Control, Linköping University, Sweden. December 2005. Supervisor: Prof. Lennart Ljung. Title of PhD thesis: *Linear Models of Nonlinear Systems.*

3. Postdoctoral position

Postdoc researcher at the ELEC department, Vrije Universiteit Brussel, Belgium. January – December 2006.

4. Qualification required for appointment as a docent

Docent in Automatic Control, Linköping University, Sweden. March 2012.

5. Current position

Associate professor (Swedish: Universitetslektor) in Automatic Control at the Department of Electrical Engineering, Linköping University, Sweden. Since September 2008. Research percentage: 50%.

6. Previous positions and periods of appointment

Research associate (Swedish: Forskarassistent) in Automatic Control at the Department of Electrical Engineering, Linköping University, Sweden. January 2007 – September 2008.

Postdoc researcher at the ELEC department, Vrije Universiteit Brussel, Belgium. January – December 2006.

PhD student in Automatic Control at the Department of Electrical Engineering, Linköping University, Sweden. December 2000 – December 2005.

Project employee (MSc thesis) at NIRA Automotive AB, Linköping, Sweden. June – November 2000.

Teaching assistant in Automatic Control at the Department of Electrical Engineering, Linköping University, Sweden. July 1999 – June 2000.

7. Interruption in research

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8. Supervision

Current students

Jonas Linder: Main supervisor since October 2012.

Ylva Jung: Main supervisor since April 2012. Co-supervisor January 2010 – April 2012.

Roger Larsson (industrial PhD student): Main supervisor since April 2012. Co-supervisor September 2007 – April 2012.

Previous students

Christian Lyzell: Main supervisor April – November 2012. Co-supervisor March 2008 – April 2012.

9. Other information of relevance to the application

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Publication list

Publications

The citation data come from Google Scholar. The five most cited publications are marked with ”(Top-5)”.

1. Peer-reviewed original articles

Y. Jung, J. Fritzin, M. Enqvist, and A. Alvandpour. Least-squares phase predistortion of a +30 dBm class-D outphasing RF PA in 65 nm CMOS. *IEEE Transactions on Circuits and Systems—Part I: Regular Papers*, 60(7):1915–1928, 2013 [Number of citations: 3]

J. Fritzin, Y. Jung, P. N. Landin, P. Händel, M. Enqvist, and A. Alvandpour. Phase predistortion of a class-D outphasing RF amplifier in 90nm CMOS. *IEEE Transactions on Circuits and Systems—Part II: Express Briefs*, 58(10):642–646, 2011 [Number of citations: 21] (Top-5)

C. Lyzell, T. Glad, M. Enqvist, and L. Ljung. Difference algebra and system identification. *Automatica*, 47(9):1896–1904, 2011 [Number of citations: 7]

M. Enqvist. Separability of scalar random multisine signals. *Automatica*, 47(9):1860–1867, 2011 [Number of citations: 0]

L. Lauwers, J. Schoukens, R. Pintelon, and M. Enqvist. A nonlinear block structure identification procedure using frequency response function measurements. *IEEE Transactions on Instrumentation and Measurement*, 57(10):2257–2264, 2008 [Number of citations: 16] (Top-5)

J. Schoukens, R. Pintelon, and M. Enqvist. Study of the LTI relations between the outputs of two coupled Wiener systems and its application to the generation of initial estimates for Wiener-Hammerstein systems. *Automatica*, 44(7):1654–1665, 2008(*) [Number of citations: 13]

M. Enqvist and L. Ljung. Linear approximations of nonlinear FIR systems for separable input processes. *Automatica*, 41(3):459–473, 2005(*) [Number of citations: 111] (Top-5)

2. Peer-reviewed conference contributions

J. Linder, M. Enqvist, and F. Gustafsson. A closed-loop instrumental variable approach to mass and center of mass estimation using IMU data. In *Proceedings of the 53rd IEEE Conference on Decision and Control*, pages 283–289, Los Angeles, California, December 2014(*) [Number of citations: 0]

M. Sadeghi Reineh, M. Enqvist, and F. Gustafsson. IMU-based vehicle load estimation under normal driving conditions. In *Proceedings of the 53rd IEEE Conference on Decision and Control*, pages 3376–3381, Los Angeles, California, December 2014 [Number of citations: 0]

J. Linder, M. Enqvist, F. Gustafsson, and J. Sjöberg. Identifiability of physical parameters in systems with limited sensors. In *Proceedings of the 19th IFAC World Congress*, Cape Town, South Africa, August 2014(*) [Number of citations: 0]

Y. Jung and M. Enqvist. Estimating models of inverse systems. In *Proceedings of the 52nd IEEE Conference on Decision and Control*, pages 7143–7148, Florence, Italy, December 2013 [Number of citations: 0]

M. Sadeghi Reineh, M. Enqvist, and F. Gustafsson. Detection of roof load for automotive safety systems. In *Proceedings of the 52nd IEEE Conference on Decision and Control*, pages 2840–2845, Florence, Italy, December 2013 [Number of citations: 0]

M. Schoukens, C. Lyzell, and M. Enqvist. Combining the best linear approximation and dimension reduction to identify the linear blocks of parallel Wiener systems. In *Proceedings of the 11th IFAC International Workshop on Adaptation and Learning in Control and Signal Processing*, pages 372–377, Caen, France, July 2013 [Number of citations: 0]

C. Lyzell, M. Andersen, and M. Enqvist. A convex relaxation of a dimension reduction problem using the nuclear norm. In *Proceedings of the 51st IEEE Conference on Decision and Control*, pages 2852–2857, Maui, Hawaii, December 2012 [Number of citations: 5]

C. Lyzell and M. Enqvist. Inverse regression for the Wiener class of systems. In *Proceedings of the 16th IFAC Symposium on System Identification*, pages 476–481, Brussels, Belgium, July 2012 [Number of citations: 0]

C. Lyzell and M. Enqvist. Sliced inverse regression for the identification of dynamical systems. In *Proceedings of the 16th IFAC Symposium on System Identification*, pages 1575–1580, Brussels, Belgium, July 2012 [Number of citations: 0]

J. Escobar and M. Enqvist. On the detection of nonlinearities in sampled data. In *Proceedings of the 16th IFAC Symposium on System Identification*, pages 1587–1592, Brussels, Belgium, July 2012 [Number of citations: 0]

R. Larsson and M. Enqvist. Sequential aerodynamic model parameter identification. In *Proceedings of the 16th IFAC Symposium on System Identification*, pages 1413–1418, Brussels, Belgium, July 2012 [Number of citations: 2]

R. Tóth, C. Lyzell, M. Enqvist, P. S. C. Heuberger, and P. M. J. Van den Hof. Order and structural dependence selection of LPV-ARX models using a nonnegative garrote approach. In *Proceedings of the 48th IEEE Conference on Decision and Control held jointly with 2009 28th Chinese Control Conference*, pages 7406–7411, Shanghai, China, December 2009 [Number of citations: 16] (Top-5)

M. Enqvist. Nonlinearity detection and impulse response estimation using a weighting approach. In *Proceedings of the 15th IFAC Symposium on System Identification*, pages 628–633, Saint-Malo, France, July 2009 [Number of citations: 0]

C. Lyzell, T. Glad, M. Enqvist, and L. Ljung. Identification aspects of Ritt's algorithm for discrete-time systems. In *Proceedings of the 15th IFAC Symposium on System Identification*, pages 681–686, Saint-Malo, France, July 2009 [Number of citations: 4]

C. Lyzell, M. Enqvist, and L. Ljung. Handling certain structure information in subspace identification. In *Proceedings of the 15th IFAC Symposium on System Identification*, pages 90–95, Saint-Malo, France, July 2009 [Number of citations: 26] (Top-5)

R. Larsson, Z. Sjanic, M. Enqvist, and L. Ljung. Direct prediction-error identification of unstable nonlinear systems applied to flight test data. In *Proceedings of the 15th IFAC Symposium on System Identification*, pages 144–149, Saint-Malo, France, July 2009(*) [Number of citations: 7]

M. Enqvist. A weighting method for approximate nonlinear system identification. In *Proceedings of the 46th IEEE Conference on Decision and Control*, pages 5104–5109, New Orleans, Louisiana, December 2007 [Number of citations: 2]

M. Enqvist, J. Schoukens, and R. Pintelon. Detection of unmodeled nonlinearities using correlation methods. In *IEEE Instrumentation and Measurement Technology Conference Proceedings*, Warsaw, Poland, May 2007 [Number of citations: 3]

3. Monographs

None.

4. Research review articles

None.

5. Books and book chapters

M. Enqvist. Identification of block-oriented systems using the invariance property. In F. Giri and E.-W. Bai, editors, *Block-oriented Nonlinear System Identification*, pages 147–158. Springer, Berlin Heidelberg, 2010 [Number of citations: 6]

6. Patents

None.

7. Open access computer programs or databases

None.

8. Popular science articles/presentations

None.

CV

Name: Martin Enqvist	**Doctorial degree:** 2005-12-09
Birthdate: 19760831	**Academic title:** Docent
Gender: Male	**Employer:** Linköpings universitet

Research education

Dissertation title (swe)		
Dissertation title (en)		
Linear Models of Nonlinear Systems		
Organisation	**Unit**	**Supervisor**
Linköpings universitet, Sweden Sweden - Higher education Institutes	Institutionen för systemteknik (ISY)	Lennart Ljung
Subject doctors degree	**ISSN/ISBN-number**	**Date doctoral exam**
20202. Reglerteknik	0345-7524/91-85457-64-7	2005-12-09

Publications

Name: Martin Enqvist	**Doctorial degree:** 2005-12-09
Birthdate: 19760831	**Academic title:** Docent
Gender: Male	**Employer:** Linköpings universitet

Enqvist, Martin has not added any publications to the application.

Register

Terms and conditions

The application must be signed by the applicant as well as the authorised representative of the administrating organisation. The representative is normally the department head of the institution where the research is to be conducted, but may in some instances be e.g. the vice-chancellor. This is specified in the call for proposals.

The signature*from the applicant*confirms that:

- the information in the application is correct and according to the instructions form the Swedish Research Council
- any additional professional activities or commercial ties have been reported to the administrating organisation, and that no conflicts have arisen that would conflict with good research practice
- that the necessary permits and approvals are in place at the start of the project e.g. regarding ethical review.

The signature *from the administrating organisation* confirms that:

- the research, employment and equipment indicated will be accommodated in the institution during the time, and to the extent, described in the application
- the institution approves the cost-estimate in the application
- the research is conducted according to Swedish legislation.

The above-mentioned points must have been discussed between the parties before the representative of the administrating organisation approves and signs the application.

Project out lines are not signed by the administrating organisation. The administrating organisation only sign the application if the project outline is accepted for step two.

Applications with an organisation as applicant is automatically signed when the application is registered.