Helsinki University of Technology Laboratory of Process Control and Automation 12

Espoo 2007

14th NORDIC PROCESS CONTROL WORKSHOP

Sirkka-Liisa Jämsä-Jounela (ed.)

TEKNILLINEN KORKEAKOULU
TEKNISKA HÖGSKOLAN
HELSINKI UNIVERSITY OF TECHNOLOGY
TECHNISCHE UNIVERSITÄT HELSINKI
UNIVERSITE DE TECHNOLOGIE D'HELSINKI

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Department of Chemical Technology
Laboratory of Process Control and Automation

Teknillinen korkeakoulu
Kemian tekniikan osasto
Prosessien ohjauksen ja automaation laboratorio

Distribution:
Helsinki University of Technology
Laboratory of Process Control and Automation
P.O. Box 6100
FI-02015 TKK
Tel. +358-9-451 3852
Fax. +358-9-451 3854
E-mail: sirkka-l@tkk.fi

ISBN 978-951-22-8913-4
ISSN 1455-4046

Multiprint Oy
Espoo

14th Nordic Process Control Workshop

It is a pleasure to welcome you to participate in the 14th Nordic Process Control Workshop, first time to Otaniemi, Espoo. This workshop follows the previous ones in Lyngby 2006, Chalmers 2004, Trondheim 2003, Turku 2001, Lyngby 2000, Stockholm 1998 etc. Over this period the NPC event has established itself as one of the largest events dedicated to process control in the Nordic countries. The NPC events have been fortunate to attract high quality papers from the key research groups of the Nordic countries and from the process industries as well.
The aim of the NPCW is to provide researchers and practitioners from industry and academia with a platform to report on recent developments in the newly emerging areas of technology and their potential applications to process automation.
This year the Nordic Process Control Award will be presented to Dr Jacques Richalet, who is widely regarded as the "grandfather of Predictive Control". The Nordic Process Control Award is presented to an international researcher of high merit, who has made lasting and significant contributions to the field of process control. The previous recipients were: Professor Manfred Morari (2006), Professor D. Gilles (2004), Professor R.Sargent (2003), Dr. Charles R. Cutler (2001), Professor Jens G. Balchen (2000), F.G. Shinskey (1998), Professor Karl Johan Åström (1997) and Howard H.Rosenbrock (1995).

Connected to the workshop a tutorial is given on the last day of the workshop (Saturday 25th of August). This year the topic of the tutorial is Fault Diagnosis and Fault Tolerant Control in Dynamic Systems. PhD students and others wishing to gain knowledge are encouraged to follow this tutorial.
The workshop is organized by the Nordic Working Group on Process Control. The Process Control group at the Department of Chemical Technology, Helsinki University of Technology are responsible for the local arrangements this year. We are pleased to announce that Academy of Finland joined the workshop as co-sponsoring entity together with Nordforsk, City of Espoo and TKK. This combination should guarantee the technical success of the NPCW07 and give especially an opportunity for the young scientists to join the Nordic control community. We hope that all the attendants at the NPCW'07 will find this event intellectually interesting and stimulating and professionally rewarding. We wish you kindly welcome!

Sirkka-Liisa Jämsä-Jounela

Otaniemi, August 2007.

PROGRAMME FOR THE 14TH NORDIC PROCESS CONTROL WORKSHOP

Thursday, August 23rd

Session I Optimization

10:30 *Economy of process control at petrochemical production plants* 2
Mauri Sourander (Neste Jacobs Oy, Finland)

10:50 *Real time production optimisation in upstream petroleum production - applied to the troll west oil rim* 4
Bjarne A. Foss (NTNU, Norway),
Vidar Gunnerud (NTNU, Norway)

11:10 *Dynamic optimization to achieve robust start-up control of a plate reactor based on sensitivity analysis* 5
Staffan Haugwitz (LTH, Sweden),
Johan Åkesson (LTH, Sweden),
Per Hagander (LTH, Sweden)

11:30 *Some possibilities of using interactive multiobjective optimization in chemical process design* 6
Kaisa Miettinen (Helsinki School of Economics, Finland),
Jussi Hakanen (University of Jyväskylä, Finland)

11:50 *Using measurements for implementation of dynamic optimization* 7
Håkon Dahl-Olsen (NTNU, Norway),
Sridharakumar Narasimhan (NTNU, Norway),
Sigurd Skogestad (NTNU, Norway)

12:10 *Implementation of optimal operation of quadratic programs using off-line calculations: Applications to heat exchanger networks and explicit MPC* 9
Henrik Manum (NTNU, Norway),
Sridharakumar Narasimhan (NTNU, Norway),
Sigurd Skogestad (NTNU, Norway)

Session II.1 Model Based Control

14:30 *Reduction of computational load associated with real-time control of distillation processes* 14
Stefan C. de Graaf (Cybernetica AS, Norway),
Pål Kittelsen (Cybernetica AS, Norway),
Heinz A. Preisig (NTNU, Norway)

14:50 *Output-error criteria in multiple-model adaptive control* 16
Jari M. Böling (ÅA, Finland),
Sharat Pathi (ÅA, Finland),
Kurt-Erik Häggblom (ÅA, Finland)

15:10 *Physical modeling, analysis and active model-based control of rotor vibrations in electric motors* 17
Juha Orivuori (TKK, Finland),
Ali Altowati (TKK, Finland),
Jozef Hrbcek (TKK, Finland),
Kai Zenger (TKK, Finland),
Antero Arkkio (TKK, Finland),
Antti Laiho (VTT, Finland),
Kari Tammi (VTT, Finland)

15:30 *Use of dynamic degrees of freedom for tighter bottleneck control* 19
Elvira Marie B. Aske (NTNU, Norway),
Stig Strand (Statoil R&D, Norway),
Sigurd Skogestad (NTNU, Norway)

15:50 *A Kalman filter tuning tool for use with model-based process control* 21
Bernt M. Åkesson (DTU, Denmark),
John Bagterp Jørgensen (DTU, Denmark),
Niels Kjølstad Poulsen (DTU, Denmark),
Sten Bay Jørgensen (DTU, Denmark)

16:10 *Ensemble kalman filtering for state and parameter estimation in a reservoir model* 23
John Petter Jensen (Statoil Research Center, Norway),
John Morten Godhavn (Statoil Research Center, Norway),
Bjarne A. Foss (NTNU, Norway)

Session II.2 Controller and Control Structure Design

14:30 *Dynamic Modeling and Control Structure Design for a Liquefied Natural Gas Process* 26
Arjun Singh (NTNU, Norway),
Morten Hovd (NTNU, Norway)

14:50 *Control Structure for Single Cell Protein Production in a U-Loop Reactor* 28
Oscar Prado Rubio (DTU, Denmark),
Sten Bay Jørgensen (DTU, Denmark)

15:10 *Flatness and steady-state control design* 30
Markku Nihtilä (University of Kuopio, Finland),
Jean Lévine (Ecole Nationale Superieure des Mines de Paris, France)

15:30 *Control structure selection for the deethanizer column from Mongstad/Statoil* 32
Eduardo Shingueo Hori (NTNU, Norway),
Sigurd Skogestad (NTNU, Norway)

15:50 *Control structure design for biological wastewater treatment plants* 34
Michela Mulas (NTNU, Norway),
Roberto Baratti (NTNU, Norway),
Sigurd Skogestad (NTNU, Norway)

16:10 *Quantitative feedback theory used on a tank reactor model* 36
Veronica Olesen (CHALMERS, Sweden),
Claes Breitholtz (CHALMERS, Sweden)

Friday, August 24th

Session III Training Simulators

08:30 *Competence development and knowledge transfer in an investment project in China. Case – start-up of a new and complex paper production line process* 40
Ismo Laukkanen (UPM-Kymmene Corporation, Finland)

08:50 *On training simulators in the chemical process industry* 41
Leif Hammarström (Neste Jacobs Oy, Finland),
Jyri Lindholm (Neste Jacobs Oy, Finland)

09:10 *ABB model editor – A framework for Modelica based on-line estimation and optimization x* 42
Alf Isaksson (ABB AB, Sweden),
Jens Pettersson (ABB AB, Sweden)

09:30 *Towards Integration of Simulation in Engineering Work Processes* 44
Juslin Kaj (VTT, Finland),
Matti Paljakka (VTT, Finland)

09:50 *Experiences of dynamic process simulation in the pulp and paper industry: Four case studies* 46
Jouni Savolainen (VTT, Finland)

10:10 *Game play in engineering education – concept and experimental results* 47
Bjarne A. Foss (NTNU, Norway),
Frank Jakobsen (NTNU, Norway),
Tor I. Eikaas (Cyberlab.Org AS, Norway)

Session IV.1 Modelling and Identification

13:00 *Comparison of experimental designs for identification of ill-conditioned systems* 50
Kurt-Erik Häggblom (ÅA, Finland),
Stefan Rosing (ÅA, Finland),
Jari Böling (ÅA, Finland)

13:20 *Straightforward identification of continuous-time process models from non-uniformly sampled data* 51
Jonas Gillberg (Preem Petroleum AB, Sweden)

13:40 *Identification of uncertain systems using support vector regression and orthogonal filter expansion* 53
Stefan Tötterman (ÅA, Finland),
Hannu T. Toivonen (ÅA, Finland)

14:00 *Dynamic modelling and simulation to overcome the initialization problem in steady state simulations of distillation columns* 54
Ivan Dones (NTNU, Norway),
Heinz Preisig (NTNU, Norway)

14:20 *Dynamic modelling of resin catalyst swelling during oxygenate reactor startup* 56
Anna Zaytseva (TKK, Finland),
Marko Laakkonen (TKK, Finland),
Petri Uusi-Kyyny (TKK, Finland),
Antti Pyhälahti (Neste Jacobs Oy, Finland),
Juhani Aittamaa (TKK, Finland)

14:40 *Dynamic model of a bubbling fluidized bed boiler* 58
Tuomas Kataja (TUT, Finland),
Matti Ylitalo (Metso Power Oy, Finland)

Session IV.2 Monitoring and Process Data Analysis

13:00 *Untapped Potential in Industrial Process Control* 62
Mats Friman (Metso Automation, Finland),
Harri Happonen (Metso Automation, Finland)

13:20 *Automatic estimation of backlash in valves* 63
Tore Hägglund (LTH, Sweden)

13:40 *Offline testing of the FTC-strategy for dearomatisation process of the Naantali refinery* 65
Sourander M. (Neste Jacobs Oy, Finland),
Liikala T. (Neste Jacobs Oy, Finland),
Vermasvuori M. (TKK, Finland),
Jämsä-Jounela S.-L. (TKK, Finland)

14:00 *A SOM-based approach for analysing and modelling a wave soldering process* 66
M.Liukkonen (University of Kuopio, Finland),
E.Havia (Elektroniikan 3K-tehdas, Finland),
H.Leinonen (Elektroniikan 3K-tehdas, Finland),
Yrjö Hiltunen (University of Kuopio, Finland)

14:20 *Data driven controller tuning* 68
Jakob Kjøbsted Huusom (DTU, Denmark),
Niels Kjølstad Poulsen (DTU, Denmark),
Sten Bay Jørgensen (DTU, Denmark)

14:40 *An embedded fault detection, isolation and accommodation system in a model predictive controller for an industrial benchmark process* 69
Markus Kettunen (TKK, Finland),
S.-L. Jämsä-Jounela (TKK, Finland)

Session V.1 Paper making & Mineral Processing

15:20 *Enhanced Causal Digraph Reasoning for Fault Diagnosis with Application on the Paper Machine Short Circulation Process* 72
Hui Cheng (TKK, Finland),
Mats Nikus (TKK, Finland),
S.-L. Jämsä-Jounela (TKK, Finland)

15:40 *Estimation of 2-dimensional variation on the basis of irregularly moving scanning sensor* 73
Johanna Ylisaari (TUT, Finland),
Kimmo Konkarikoski (TUT, Finland),
Risto Ritala (TUT, Finland)

16:00 *Improving profile estimation on paper and board machines* 75
Merja Mäkelä (University of Applied Sciences, Kotka, Finland),
Ville Manninen (LUT, Finland),
Piotr Ptak (LUT, Finland),
Miika Tolonen (LUT, Finland),
Johanna Ylisaari (TUT, Finland)

16:20 *Software for filtration data analysis (FDA)* 76
Nina Salmela (Hyötypaperi Oy, Finland),
Marja Oja (TKK, Finland)

16:40 *Experiences in charge volume measurement and the potential of modeling* 77
Jussi Järvinen (Outotec Oyj, Finland),
Heikki Laurila (Outotec Oyj, Finland),
Jarkko Karesvuori (Outotec Oyj, Finland),
Peter Blanz (TKK, Outotec Oyj, Finland)

Session V.2 Control Applications

15:20 *Optimal operation of a 4-product integrated kaibel column* 80
Jens Strandberg (NTNU, Norway),
Sigurd Skogestad (NTNU, Norway)

15:40 *Compensating the transmission delay in networked control systems* 81
Nikolai Vatanski (TKK, Finland),
Georges J.P (Henri Poincaré University, France),
Rondeau E. (Henri Poincaré University, France),
Auburn C. (Henri Poincaré University, France),
S.-L. Jämsä-Jounela (TKK, Finland)

16:00 *Requirements for modern advanced control technologies in the hydrocarbon industry* 82
Samuli Bergman (Neste Jacobs Oy, Finland),
Teemu Liikala (Neste Jacobs Oy, Finland)

16:20 *Optimization and simulation application for expandable polystyrene batch process* 84
Mikko Heikkinen (University of Kuopio, Finland),
Teri Hiltunen (University of Kuopio, Finland),
Ville Nurminen (StyroChem Ltd , Finland),
Yrjö Hiltunen (StyroChem Ltd , Finland)

16:40 *Gain scheduling control in secondary air control system* 86
Kimmo Leppäkoski (University of Oulu, Finland),
Jari Mononen (University of Oulu, Finland)

17:00 *Identifiability analysis and qualitative experimental design for synthetic biological networks* 88
Florin Paul Davidescu (DTU, Denmark),
Sten Bay Jørgensen (DTU, Denmark)

Posters

Analysis of CSTR by entropy generation minimization 90
João T.Manzi (Catholic University of Pernambuco, Brazil),
Ed. Carrazzoni (Catholic University of Pernambuco, Brazil)

Volterra model based predictive control, application to a PEM fuel cell 92
Fernando Dorado (Universidad de Sevilla, Spain),
Carlos Bordóns (Universidad de Sevilla, Spain)

Potential of dry line information to the control of paper machine 93
Antti J. Niemi (TKK, Finland),
Sami Kiviluoto (TKK, Finland)

Balancing material and energy flows 94
Ville Laukkanen (Oy Indmeas Ab, Finland)

Embedded Control and Monitoring Systems in Production Machine Networks, EMPRONET 95
Mikko Huovinen (TUT, Finland),
Yrjö Majanne (TUT, Finland)

A simple dynamic model of the paper machine short circulation process 96
Mats Nikus (TKK, Finland),
Hui Cheng (TKK, Finland),
S.-L. Jämsä-Jounela (TKK, Finland)

Network of Integrated Biomeasurements and Control via Intranet and SMS 97
Salonen K. (TKK, Finland),
Kiviharju K. (TKK, Finland),
Eerikäinen T. (TKK, Finland)

Simulation of Fault Scenarios Using a Paper Machine Simulator 98
Vesa-Matti Tikkala (TKK, Finland),
Mats Nikus (TKK, Finland),
Hui Cheng (TKK, Finland),
Sirkka-Liisa Jämsä-Jounela (TKK, Finland)

Design, development and testing of an online process monitoring system 99
Lari Tuononen (TKK, Finland),
Sirkka-Liisa Jämsä-Jounela (TKK, Finland)

FULL PAPERS

Physical modeling, analysis and active model-based control of rotor vibrations in electric motors 102
Juha Orivuori (TKK, Finland),
Anssi Sinervo (TKK,Finland),
Ali Altowati (TKK, Finland),
Jozef Hrbcek (TKK, Finland),
Kai Zenger (TKK, Finland),
Antero Arkkio (TKK, Finland),
Antti Laiho (VTT, Finland),
Kari Tammi (VTT, Finland)

Controlled Variables Selection for a Biological Wastewater Treatment Process 108
Michela Mulas (NTNU, Norway),
Roberto Baratti (NTNU, Norway),
Sigurd Skogestad (NTNU, Norway)

Dynamic model of a bubbling fluidized bed boiler 114
Tuomas Kataja (TUT, Finland),
Yrjö Majanne (TUT, Finland)

Offline testing of the FTC-strategy for dearomatisation process of the Naantali refinery 120
Sourander M. (Neste Jacobs Oy, Finland),
Liikala T. (Neste Jacobs Oy, Finland),
Vermasvuori M. (TKK, Finland),
Jämsä-Jounela S.-L. (TKK, Finland)

A SOM-based approach for analysing and modelling a wave soldering process 126
M.Liukkonen (University of Kuopio, Finland),
E.Havia (Elektroniikan 3K-tehdas, Finland),
H.Leinonen (Elektroniikan 3K-tehdas, Finland),
Yrjö Hiltunen (University of Kuopio, Finland)

An embedded fault detection, isolation and accommodation system in a model predictive controller for an industrial benchmark process 130
Markus Kettunen (TKK, Finland),
S.-L. Jämsä-Jounela (TKK, Finland)

Enhanced Causal Digraph Reasoning for Fault Diagnosis with Application on the Paper Machine Short Circulation Process 136
Hui Cheng (TKK, Finland),
Mats Nikus (TKK, Finland),
S.-L. Jämsä-Jounela (TKK, Finland)

Estimation of 2-dimensional variation on the basis of irregularly moving scanning sensor *142*
Johanna Ylisaari (TUT, Finland),
Kimmo Konkarikoski (TUT, Finland),
Risto Ritala (TUT, Finland)

Improving profile estimation on paper and board machines *148*
Merja Mäkelä (University of Applied Sciences, Kotka, Finland),
Ville Manninen (LUT, Finland),
Piotr Ptak (LUT, Finland),
Miika Tolonen (LUT, Finland),
Johanna Ylisaari (TUT, Finland)

Compensating the transmission delay in networked control systems *153*
Nikolai Vatanski (TKK, Finland),
Georges J.P (Henri Poincaré University, France),
Rondeau E. (Henri Poincaré University, France),
Auburn C. (Henri Poincaré University, France),
S.-L. Jämsä-Jounela (TKK, Finland)

A Modeling and Optimization Tool for the Expandable Polystyrene Batch Process *159*
Mikko Heikkinen (University of Kuopio, Finland),
Teri Hiltunen (University of Kuopio, Finland),
Ville Nurminen (StyroChem Ltd , Finland),
Yrjö Hiltunen (StyroChem Ltd , Finland)

Gain scheduling control in secondary air control system *164*
Kimmo Leppäkoski (University of Oulu, Finland)

Volterra model based predictive control, application to a PEM fuel cell *169*
Fernando Dorado (Universidad de Sevilla, Spain),
Carlos Bordóns (Universidad de Sevilla, Spain)
J.Gruber (Universidad de Sevilla, Spain),
E.F.Camacho (Universidad de Sevilla, Spain)

Network of Integrated Biomeasurements and Control via Intranet and SMS *175*
Salonen K. (TKK, Finland),
Kiviharju K. (TKK, Finland),
Eerikäinen T. (TKK, Finland)

Session I: Optimization

ECONOMY OF PROCESS CONTROL AT PETROCHEMICAL PRODUCTION PLANTS

M. Sourander

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Keywords: Economy, Process Control, Optimization, Dynamic, Closed loop, Nonlinear, Process models, Adaptation.

Production plant operation in the hydrocarbon business sector has been recognized as a very challenging one due to the complexity of the processes involved and even more so due to the complexity of the economics and logistics involved. There are, however, a number of opportunities typically present to make the objective of economic optimization worthwhile, in particular if supported by an underlying structure of process control applications streamlined to fulfill the same task. In the relatively recent past of 20 years we have experienced in our control applications a gradual shift from control problems to profit maximization control problems. Until recently this shift would have implied the use of a separate optimization layer in the process control hierarchy, but the invention of our dynamic real-time optimization (DRTO), involving both the control and the dynamic economic optimization has completely changed the trend. Advanced process control applications involving multivariable predictive control require much effort in installing and commissioning phases; the attributable costs are for any practical control application of such a magnitude, that a resulting yearly benefits have to match the costs. Our experience and several authors have shown that a more precise control to target *per se* seldom can attribute any realizable economic benefit for a plant. However, a good and robust control is a prerequisite for introducing such moves to the process, that the operating conditions can be changed on a more permanent footing, providing a tangible improvement to the profit. Which set of such moves will give the best economical result is of course a typical optimization problem in the dynamic domain. The optimized moves should not, however, bring the process conditions to a regime outside the safe operating window defined by a number of constraints. The original "simple" control problem is now replaced by a simultaneous problem of control, constraint control and economic optimization with a scope several times the original one; but this new "controller" has the property of assuring an economic benefit for the user. It is quite easy to see the rational behind the recent trend: why bother with a simple controller when you can get so much more from a full-blown DRTO with the costs in the same order of magnitude. Therefore, for this industry sector, there is currently very little interest for classical advanced control which is regarded as a commodity, but the interest has shifted to the scope of control providing economic constrained optimization instead.

Real-time economical optimization of production plants previously relied on steady state process models. In chemical engineering, process models are only approximate, and need to be adapted to observed process measurements as often as possible. Steady-state models require that the process is in a steady state before model adapting can be carried through. Because real plants are normally in transient states, such models could traditionally be adapted to measurements only occasionally. This type of delay for the inherently dynamic processes is unacceptable for many plants; consequently we have seen that during the 2000's 80% of our new installed advanced control applications have been of the type of profit maximizing process control problems. The new closed loop dynamic realtime optimization technology of Neste Jacobs Oy naturally optimizes the plants also during transient states. The technology works in realtime, which contributes to quickly reaching optimum.

The competitive edge for most process plants is due to their ability to quickly maximize the profit. The agility of the plant adaptation to opportunities may become decisive for its success, quite like the requirements for modern business. To a large extent this is attributable to the dynamics in throughput. The plant economy is as dynamic as the process and need also to be evaluated in real time. The complex network of cause and effect has to be solved simultaneously to trade off the different final economics. Naturally, the feedstock and product price fluctuations affect substantially the optimum production strategy. Maximizing process plant profit repeatedly has led to solutions where production volume profit clearly dominates over the recovery and utility costs at the optimum constrained by a number of safety- and quality-related variables. A typical consistent optimum policy of using as much utilities as required to meet the product specifications and ride the constraints as tightly as possible to accommodate maximum production rates generally prevails. The optimization of simultaneous tradeoff opportunities of this nature allover a plant is the essence of optimal resource allocation, including the tradeoff between the loads of competing processes. Although some plants may operate occasionally at less than full capacity and the control applications then act to make the most profitable selection of independent variables, it can be anticipated that most often the economics are driving to maximum safe use of the installed capacity. Consequently, the plant should operate most of the time against a number of different simultaneous constraints and control requirements. In this kind of constrained regime the ability of DRTO technology of riding the frequent transient states, becomes doubly important and will swiftly move to the optimal production. The DRTO has also to immediately recognize any operator major actions, adapt to the new process states, and make the resulting optimization moves.

Feedstocks and products often vary either dynamically or from batch to batch and may be further subject to subsequent dynamically varying mixing in storage area tanks and feed systems. Generally, recycle streams are necessary to drive processes to acceptable conversions and recoveries. This dynamically affects the composition of process streams and subsequent processing characteristics.

The problem sizes differ remarkably from case to case: A simple distillation column control for instance has only about 30 variables involved whereas a large plant application has more than 500 variables to consider.

A particularly interesting case is when several autonomous MPC:s are harnessed to work together with a coordinating DRTO application. Such an application has recently been discussed by Vettenranta *et al*. The benefit of this type of application is to distribute coherently the effort in a more robust framework. It is important, that each autonomous MPC has the constraint handling and profit pushing properties as does the coordinating application.

Our company, including its predecessors, has been in the advanced control business since 1980's and has delivered more than hundred applications worldwide, most of which are multivariable control applications. Since 2000 we have mostly concentrated in providing DRTO applications due to clear customer preference. There are presently in use several DRTO applications in petrochemical, chemical, and refinery processes with excellent results. All of these are of considerable size. The results obtained from two of them will be discussed as examples.

The first of the DRTO application examples, started in 2003, is in the Ethylene Plant of Borealis Polymers Oy, Porvoo, Finland. The objective function for the ethylene plant DRTO is the plant profit (gross margin before fixed costs), evaluated once per minute. The DRTO solution for the plant was designed to address the unexploited benefit opportunity presented by plant dynamics. The DRTO has been in continuous use since 2004 and the experience is outstanding. The delivery and commissioning in two project phases worked well as planned. The DRTO was online for 99.7 % of the time in 2005. In 2004 a new yearly ethylene production record of 327.000 t was made. The improvement to the previous record was almost 10 per cent. The benefits obtained from the project surpassed the expected ones; the economic benefit during 2004 was 12.5 million US$. This gives a calculated payback time of less than a month.

The second example, started 2005, is the Butadiene Plant of Borealis Polymers Oy, Porvoo, Finland. In this plant the profit is directly related to the production volume of the main product Butadiene, which makes the profit optimization much more straightforward than in the Ethylene plant case. The main objective was to reach the maximum performance in minimum time. The project time was three months and the optimization resulted in an increase of butadiene volume by 7 to 10 per cent giving the project a payback time of about two months. The service factor has been about the same as in the previous case and a new production record was made in winter of year 2007.

Neste Jacobs' NAPCON DTRO is a new powerful technology, which surpasses the traditional steady-state realtime optimization (RTO) in its ability to both handle the dynamics of process plants and make action in almost real-time. The development of the DRTO technology has made it possible to optimize in realtime the profit of large plants in transient states as a result from using dynamic models. DRTO executes each minute and drives the process swiftly to optimum even during transients, when the action is most needed. The nonlinear optimization is based on sparse matrix handling, designed to provide high efficiency for solving optimization problems subject to fulfilling simultaneously the required control objectives. The property predictor, integrated with a recipe system, is used to provide realtime model-based predictions of such process and product quality parameters, which are not available online or are available only intermittently. The recipe system is particularly useful for cases, in which the same process equipment is used for multiple purposes, like several feedstocks or product grades.

The technology has under several years of successful use in several plants proven its robustness and performance. It has also proved to be a precise solution to the real problems in the modern petrochemical industry plant control and optimization needs.

Sourander, M. *et al* (1984) Control and optimization of olefin-cracking heaters, *Hydrocarbon Processing*, ***V63**, N6, June, 1984, p. 63.*

Vettenranta, J. *et al* (2006) Dynamic real-time optimization increases ethylene plant profits, *Hydrocarbon Processing*, ***V85**, N10, June, 2006, p. 59.*

Bergman, S. *et al* (2007) Butadiene plant DRTO controls, *Automaatio 2007, Proceedings of the Finnish Society of Automation (in Finnish).*

Real time production optimisation in upstream petroleum production
- Applied to the Troll West oil rim

Bjarne A. Foss[1], Vidar Gunnerud
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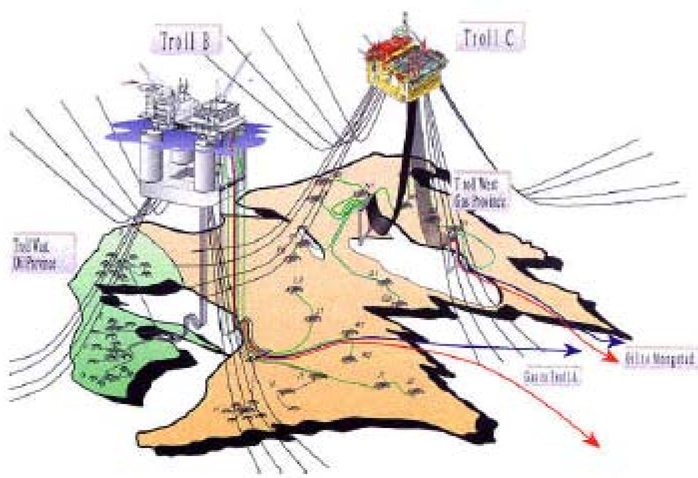
Upstream petroleum production systems are usually quite complex consisting of many wells, pipelines and processing units. The figure below shows a sketch of the Troll West oil field with more than 50 wells feeding the pipelines and downstream processing units. Optimisation is performed on the life-time horison of the hydrocarbon reservoir, typically many years, as well as on shorter time horisons. In this study we focus on short term optimisation in the range of days and weeks. This requires models of each well and the pipeline system. Downstream processing equipment is not included in the present study.



The presentation will first discuss appropriate well models, in particular how models (usually denoted proxy models) can be generated from from high fidelity reservoir simulator models. An important issue in the Troll West case is the inclusion of gas coning effects, a phenomenon which can limit production significantly. Second, alternative formulations of the optimisation problem will be discussed and assessed. These include a nonlinear programming problem and a mixed integer formulation. Third, alternative solutions methods are discussed with emphasis on the Lagrangian decomposition technique which has certain merits because of the network structure of the present problem.
Finally, some results based on models and data from the Troll West field will be presented and further research challenges discussed.

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Dynamic optimization to achieve robust start-up control of a plate reactor based on sensitivity analysis

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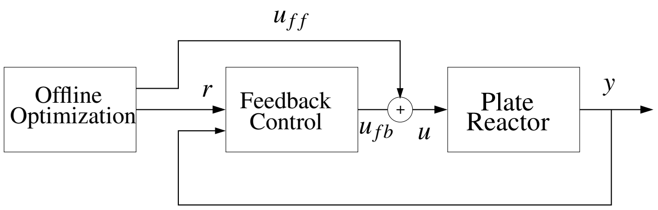

Fig. 1. General block diagram for the start-up control with offline optimization and online feedback control.

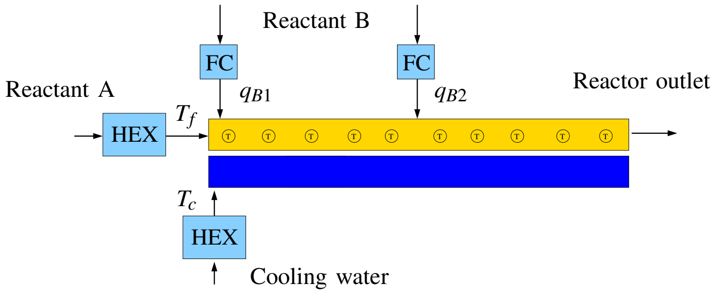

Fig. 2. The reactor shown as a schematic tubular reactor. There are four inflows to the process and there is one manipulated variable for each inflow; q_{B1}, q_{B2}, T_f and T_c.

I. Extended Abstract

In this paper, start-up of a plate reactor with an exothermic reaction is considered, see also (Haugwitz *et al.*, 2007). In this paper, we consider off-line optimization of start-up trajectories. The size and complexity of the problem, in combination with fast dynamics, complicate on-line solution of the optimal control problem in real-time. The off-line computed optimal trajectories are then implemented as feedforward and reference signals to a feedback controller, see Figure 1.

In this paper, the Alfa Laval Plate Reactor (Alfa Laval AB, 2006), is considered. This type of reactor is conceptually a combination of a tubular reactor and a plate heat exchanger. The key concept is to combine efficient micro-mixing with excellent heat transfer into one operation. In Figure 2, the plate reactor is schematically illustrated as a tubular reactor. With multiple injection points, the heat release from the exothermic reaction can be distributed along the reactor, thus improving the productivity despite constraints on the reactor temperature. A heat exchanger pre-heats the reactant feed A and another heat exchanger cools the cooling water to desired inlet temperature. Two flow control loops ensure that the desired amount of B is fed into the reactor.

The problem is challenging, since the process is highly non-linear, and subject to uncertainty, especially in the reaction kinetics. Limited bandwidth of the feedback controller requires that the optimization gives optimal solutions with low sensitivity to uncertainty. Special attention is given to the problem of formulating an optimal control problem based on physical insight to reduce the sensitivity of the solution, thus increasing the overall robustness of the closed loop system.

In this paper, we consider a *simultaneous* method for solving the dynamic optimization problem, see e.g. (Biegler *et al.*, 2002), where both the control variables and the state variables are discretized. Since the dynamics must be discretized with sufficient accuracy, the resulting NLP is large but sparse. Recent advances in specialized algorithms have increased the applicability of the simultaneous methods, (Wächter and Biegler, 2006). There are two main reasons for choosing a simultaneous method in this case. Firstly, the simultaneous methods have good numerical stability properties, which is important in this case, since the system dynamics is unstable in some operating conditions. Secondly, one of the most important elements of the optimization problem is a temperature path constraint, which is straight forward to enforce using a simultaneous method.

The resulting solutions are evaluated in Monte Carlo simulations. The study shows that introducing concentration constraints on the injected chemical in combination with high frequency penalties on the control signals lead to less sensitive optimal solutions, thus yielding a more robust start-up.

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SOME POSSIBILITIES OF USING INTERACTIVE MULTIOBJECTIVE OPTIMIZATION IN CHEMICAL PROCESS DESIGN

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Problems in chemical engineering, like most real-world optimization problems, typically, have several conflicting performance criteria and they often are computationally demanding, which sets special requirements on optimization methods used. In this paper, we point out some shortcomings of widely used basic methods of multiobjective optimization. As an alternative, we suggest using interactive approaches where the role of a decision maker or a designer is emphasized. Interactive multiobjective optimization has been shown to suit well for chemical process design problems because it takes the preferences of the designer into account in an iterative manner that enables a focused search of the best compromise between the conflicting criteria. For this reason, only those solutions that are of interest to the designer need to be generated making this kind of approach computationally efficient. Furthermore, during the interactive solution procedure the designer can learn about the interrelationships among the performance criteria. In addition to describing the general philosophy of interactive approaches, we discuss the possibilities of interactive multiobjective optimization in chemical process design and give some examples of interactive methods to illustrate the ideas. Finally, we demonstrate the usefulness of interactive approaches in chemical process design by summarizing some reported studies related to, for example, paper making and sugar industries.

Using Measurements for Implementation of Dynamic Optimization

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Optimal operation of chemical processes can in general be formulated as a dynamic optimization problem. Most chemical processes are run at steady state and such a complicated description is not needed. Other processes though, are transient in nature, and the dynamic behavior must be considered (Narasimhan and Skogestad, 2007). Such transient processes may be start-up and shut-down of continuous plants, grade changes or batch operations. In mathematical terms a dynamic optimization problem can be formulated as follows:

$$\min_{u(t),t_f} J(x(t), u(t), t), \tag{1}$$

$$\text{s.t. } \dot{x} = f(x, u, d), \tag{2}$$

$$h(x, u, d) = 0, \tag{3}$$

$$g(x, u, d) \leq 0, \tag{4}$$

$$e(x(t_f)) \leq 0. \tag{5}$$

The solution of such a problem is discontinuous in nature and consists of a set of arcs.

The optimal solution should not be implemented in an open-loop manner in most cases because of uncertainty and unknown disturbances. It may be assumed that for small disturbances, the structure of the optimal solution stays the same. With structure we mean the number of arcs and their qualitative shapes. The optimal solution is often very sensitive to the switching times. An open-loop implementation with time-controlled switches between the arcs may easily lead to infeasibility or severe loss with regard to the true optimal solution.

The implementation of optimal control should be based on measurements to ensure robustness of the plant. The implementation can follow two different paradigms (Narasimhan and Skogestad, 2007);

- on-line optimization where measurements are used mainly to update the process model,
- off-line compuation of optimal solutions and implementation using feedback control based on measurements.

In self-optimizing control we follow the latter paradigm. On-line optimization suffers from considerable computational load, which is relieved when critical computations are done off-line.

Self-optimizing control is when near-optimal operation can be achieved with constant set-points, without the need to re-optimize when disturbances occur (Skogestad, 2004). The same definition is utlized for dynamic systems, where one self-optimizing variable is needed for each arc.

As discussed by Narasimhan and Skogestad (2007) the identification of self-optimizing control structures involves a sequence of steps. First, the structure of the optimal solution must be determined For this, reliable numerical methods exist (Bausa, 2000).

When the structure is known, good self-optimizing variables should be found, which are such that their optimal values do not differ much under disturbances. The Hamiltonian function from optimal control theory is such a variable for a free end-time problem. It then takes the value zero along the optimal path (Naidu, 2000). This variable can in general not be measured, and therefore we have to look for other self-optimizing variables. Three examples are considered;

1. A simple problem with one input and two states is used to illustrate the method.

2. A comparison with NCO tracking is made, using the fed-batch bio-reactor example of (Srinivasan et al., 2002).

3. The method is extended to larger systems in a ternary batch distillation example.

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Implementation of optimal operation of quadratic programs using off-line calculations: Applications to heat exchanger networks and explicit MPC

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The computational effort involved in the solution of real-time optimization problems can be very demanding. Hence, simple but effective implementation of optimal policies are attractive. The main idea is to use off-line calculations and analysis to determine the structure and properties of the optimal solution [1].

There are two main paradigms when it comes to implementation of the optimal solution [1]:

Paradigm 1 On-line optimizing control where measurements are primarily used to update the model. With arrival of new measurements, the optimization problem is resolved for the inputs.

Paradigm 2 Pre-computed solutions based on off-line optimization. Typically, the measurements are used to (indirectly) update the inputs using feedback control schemes.

In addition to be low on computing demand, paradigm 2 offers a number of additional advantages, including robustness, simplicity and reduced cost for modelling, implementation and maintenance.

In this work we will focus on solving the following problems:

P1 Determine the structure of the optimal solution. Typically, this involves regions where different set of constraints are active.

P2 Find good self-optimizing controlled variables c associated with the unconstrained degrees of freedom that satisfy the following [2]:

- The optimal value c_{opt} is only weakly dependent on disturbances.
- Implementation errors in these variables does not result in a large loss or equivalently the optimum with respect to c is "flat".

P3 Determine a switching policy between different regions.

These items are a subset of items listed in [1] for possible results for paradigm 2.

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In this work the emphasis will be on a class of problems that can be formulated as parametric quadratic programs (PQP) [3]:

$$
\begin{aligned}
& V(\theta) = \min\nolimits_{x \in \mathbb{R}^n} \tfrac{1}{2} x^{\mathrm{T}} H x + c^{\mathrm{T}} x, && (1)\\
\text{subject to} \quad & \widetilde{A} x = \widetilde{b} + \widetilde{S}\theta, && (2)\\
& \underset{\sim}{A} x \le \underset{\sim}{b} + \underset{\sim}{S}\theta. && (3)
\end{aligned}
$$

Here x is a vector of decision variables, and θ is a vector of disturbances. In the above formulation $x = (x_{\text{state}}, u)$.

This problem has attracted a lot of attention recently because the explicit MPC problem can be formulated in this way [3]. When there is no noise on the measurements there exists an exact solution to the problem.

The solution of a PQP problem will consist of a set of polyhedral regions (critical regions) in the parameter space for which the active set remains unchanged. For a PQP the optimizers will be piecewise affine functions of the parameters [3]. Each critical region can be described by:

$$
A_e x = b_e + S_e \theta, \tag{4}
$$
$$
y = Gu + G_\theta \theta, \tag{5}
$$

where (4) is the equality and active inequality constraints in the current region, and (5) is the function from inputs and disturbances to the measurements.

The degrees of freedom available for economic optimisation will in each region be given by the size of x minus the rank of A_e.

A PQP problem can be solved using for example the MPT toolbox [4].

Solving the PQP implies finding a solution to P1.

In critical each region the active constraints should be controlled for optimal operation [2]. If there are remaining degrees of freedom the null-space method [5] can be used to find self-optimizing controlled (soc) variables c in each region. Performing this steps solves P2.

In each critical region the active set remains unchanged. Entering a region with less degrees of freedom than the current region can be detected by saturation. Due to the properties of the soc variables these can be used to detect when one is entering a region with more unconstrained degrees of freedom. This implies that an optimal switching policy can be found, and a solution to P3 is provided.

The ideas will be demonstrated on several examples including static optimization problems such as optimal operation of heat exchanger networks (HENs) and dynamic optimization problems such as the explicit MPC problem. The examples will be HENs which can be written as QP problems.

For the explicit MPC example one can use the soc's as indicators for change of active sets, giving an alternative to state estimation. For the HEN example the need to reoptimize when large disturbances occur is eliminated as the whole parameter space is explored in advance and an efficient operation policy is already available.

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Session II.1: Model Based Control

REDUCTION OF COMPUTATIONAL LOAD ASSOCIATED WITH REAL-TIME CONTROL OF DISTILLATION PROCESSES

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Cybernetica AS, based in Trondheim (Norway), has joined forces with 4 universities and 2 enterprises in a European project called PROMATCH. This project deals with reduction of computational load associated with real-time advanced control of chemical processes. The background of the project is that computations that are carried out by model-based controllers often involve substantial computational loads. This weakens controller performance and therefore prevents practical implementations of these controllers.

In general, high computational loads are caused by inadequate DAE models and inefficient algorithms. Much research has already been carried out on reducing these loads. This research has resulted in various computationally efficient control algorithms and methods to change either control problems or models. Table 1 globally identifies typical causes of high computational load and methods to remove them.

Serving as a case-study, the computational loads associated with the advanced control of one particular distillation process is currently being studied. Such an advanced controller should respond quickly and adequately to any changes in process conditions, so that fewer impurities in product streams, an increase of the throughput near process constraints and faster start-up and shutdown are achieved.

A mixture of several causes of high computational load is present in distillation problems. Researchers at Cybernetica, the Norwegian University of Science and Technology in Trondheim (Norway) and Reinisch-Westfälische Technische Hochschule in Aachen (Germany) are working on the combined application of some methods listed in Table 1 with the goal to reduce this load considerably.

In this presentation, the focus is on problems containing a large number of state equations (first problem in Table 1). To this end, partitioning and lumping of the state equations in distillation models are applied. This is a method that is physically easy interpretable when it is applied - and therefore to the researchers favourable over other relevant methods that are mentioned in Table 1.

Table 1: Typical causes of high computational load and methods to remove them

Problem contains a large number of state equations
- Balanced truncation [1], [2]*
- (Balanced) proper orthogonal decomposition [3], [2]*
- State transformation based on self similar solutions of the state equations [4], [5]*
- Partitioning and lumping of state equations [6], [7]*, [8]
- Partitioning of equations using existing knowledge about process [9]

Problem contains a system of differential and algebraic equations with a high index number
- Differentiation of the algebraic equations [10]
- Representing original DAE system by another model [11]

Problem contains complex nonlinear algebraic equations
- Transforming implicit equations as much as possible to explicit equations
- Representing algebraic equations by other models, e.g. neural networks [12]
- Storage and retrieval of solutions from tables [13]

Solving the problem involves repeated computation of large Jacobian matrices
- Linearization of non-linear systems by truncation of Taylor-expansions
- State-feedback linearization [14]
- Increasing the efficiency of computing Jacobians by e.g. detecting sparse structures and applying automatic differentiation

Solving the problem involves repeated revision of optimal trajectories
- Applying neighbouring extremal control [15]
- Applying self-optimizing control [16]
- Tracking necessary conditions of optimality [17], [18]

* Reference to distillation-associated problems

The basic ideas of the method and differences between variants of the method will be explained, both mathematically and physically. The effect of the method on computational load will also be explained. Furthermore, results of the application of this method to the distillation model will be demonstrated.

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Output-Error Criteria in Multiple-Model Adaptive Control

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Extended Abstract

Multiple-model adaptive control (MMAC) is a variation of adaptive control where, instead of fitting the model parameters directly to data, one chooses the model which best describes the data from a prespecified set of models. For each model there is an associated controller that is used for feedback control whenever the model is selected. Compared to traditional adaptive control, the robustness is increased in several ways in MMAC. The allowed models and controllers are prespecified, thus limiting the controller behavior. Furthermore model switching is not allowed all the time, only when another model is found significantly better than the current used model, thus reducing drift under periods of low excitation. Finally, one can treat non-stationary disturbances in a rather nice way in MMAC.

Conventional prediction-error based identification typically emphasizes high-frequency behavior of the plant. This is so because the model error is weighted with the inverse of the noise model, and the noise model is typically a low-pass filter. In output-error identification the noise model is by definition equal to identity, so even weighting of all frequencies is obtained.

In the current study output-error criteria are used as a measure of model goodness in a multiple-model adaptive controller. Non-stationary disturbances introduced some problems, as an output-error model does start predictions at time 0, while a prediction-error model does predict the change from current output. So if one has non-stationary drift one typically gets very slow reactions, as one need to forget much more old behavior than in a prediction-error case. A number of alternative improvements related to this are suggested.

The performance of the different output-error based MMAC is compared to standard prediction error based MMAC using both linear and nonlinear simulations.

Physical Modeling, Analysis and Active Model-Based Control of Rotor Vibrations in Electric Motors

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EXTENDED ABSTRACT

Vibration control of different engineering applications is growing all the time, as the precision and accuracy demands for different engineering solutions are getting more stringent. As the allowed tolerances become smaller, the vibrations have a bigger impact on the total system. For example, air-gaps in electric drives need to be smaller to increase the overall efficiency of the machine, yet the vibrations hinder this goal as the air-gap varies along to the vibrations. Passive damping has been widely used for many different applications, but it can only be used to dampen vibrations at a certain frequency. In high-performance control passive damping is then inadequate and an active control method is needed. In active control an external force is excited to the system according to a control law with the goal to minimize the vibrations. Active control is becoming more and more important all the time, and new research efforts are introduced into this field. It can be designed with traditional control methods to a certain extent, but the harmonics of the main vibration frequencies and the dynamic nature of the load disturbance may need more sophisticated control methods.

In this paper active control of rotor vibrations in electrical motors is considered. The driving speed of the motor is limited by the critical frequency that depends on the size and weight of the rotor. An all purpose motor would bring savings for the manufacturing company and the customer as the motor doesn’t have to be designed for a certain operation condition only. Specifications for any application to be designed also become simplified as all the drive speeds are available instead of just a single speed.

The idea in the vibration controls to be introduced is to generate a control force to the rotor through extra windings in the stator. This actuator generates a magnetic field that induces a force negating the disturbance force exited by the mass imbalance of the rotor.

The modeling process is initialized by the first principles of electromechanical systems. A separate electric model is created for the actuator generating control force with a magnetic field. An electromechanical model is then formed for the rotor that transfers the input forces into displacements. In addition to the physical model of the system a FEM-model is created to help in the validation of the results, and to generate black box data. The next phase is to manipulate the physical models in such way that they become standard transfer-function matrices. Alternatively, an augmented state-space representation that includes the actuator, disturbance and rotor models in a single composed model can be used. The state-space representation can be constructed by selecting the state-variables from the physical model that yields an exact model of the system with some couplings between inputs. The other approach is to identify the system from the data achieved from FEM-simulations, which describe the system behavior very accurately. By identification the model can be simplified such that the couplings between inputs disappear, but the model still describes the system well enough. When the reduced model is ready, it is validated by simulations against the FEM-model. The FEM-model is very slow to simulate, so a Simulink-model with approximately the same behavior is needed.

Further analysis on the problem will be made in order to find out what kinds of control approaches are possible to this problem. The analysis includes both frequency domain and structure analysis of the system, thus revealing the theoretical limitations for control performance.

Several different modern control methods will be tested to dampen the vibrations; also traditional methods will be used where possible. A basic compensator is designed to compensate the vibration by using the frequency domain analysis. State feedback will be used with state-observer that estimates the hidden states and the dynamics of the disturbances. A model predictive control problem will be implemented and tested. Other control methods include LQ (Linear Quadratic), Robust-control and QFT (Quantitative Feedback Theory) in frequency domain.

All control designs achieved for the system are tested and validated by using the FEM-model. A control loop with controllers designed in Simulink is included in the FEM-model and simulated. In order for the control models to be reliable they must have similar behavior in FEM-environment as they did in Simulink.

This work presents common problems arising in the vibration control of rotors and some possible solutions to overcome them. This research is driven by the increased need for high-performance control for oscillating systems, and the lack of standardized approaches for this kind of control problems. Even as the results are only for the rotor vibration control, the methods achieved can be used basically in any vibration control problem as long as certain conditions are met. For example, vibration control of paper winders is an interesting topic of current research by the group.

Use of dynamic degrees of freedom for tighter bottleneck control

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Extended abstract

In many cases the prices and market conditions are such that optimal operation of the plant is the same as maximizing plant throughput. In the special but important case of a linear network, the *max-flow min-cut* theorem (Ford and Fulkerson 1962) states that optimal operation is the same as maintaining maximum flow through the bottleneck(s).

In terms of realizing maximum throughput there are two issues, first, identify the bottleneck(s), and second, implement maximum throughput at the bottleneck(s). The optimal way to maximize throughput is to place the throughput manipulator (TPM) at the bottleneck, (Skogestad 2004). If the bottleneck does not move, this can be realized with single-loop controller from the TPM to the bottleneck. However, if the bottlenecks move this requires reassignment of the loops, not only the TPM loop, but also the inventory loops to ensure self-consistency (Price and Georgakis 1993). This is undesirable. A better approach is then to use a multivariable coordinator controller since input and output constrains are directly included in the problem formulation.

Aske *et al.* (2007) propose a coordinator MPC to realize maximum throughput. The plant throughput is coordinated by using feed flows and crossover rates, and can be viewed as degrees of freedom which is not available to the local MPC, since the plant throughput can not be decided without looking at the whole plant. In the proposed approach, each unit calculates its maximum capacity based on the end prediction in the local MPC, which is installed at each unit. This leads to a smart decomposition of the problem. The controlled variables (CVs) in the coordinator are remaining capacity for each unit (low limit with high priority) and total plant feed

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(high, unreachable set point with lower priority). Hence, the coordinator will maximize the throughput while keeping the units within its constraints. Note that the set points to the local MPCs are not changed, only the feed rate, and therefore there is an assumption of near optimal operation of the local MPCs.

The proposed coordinator MPC shows good results in a simulation study (Aske *et al.* 2007) and there is ongoing implementation of this concept at the Kårstø gas processing plant. Even with this concept there may be long control loops from the manipulated variable to the bottleneck, leaving it difficult to obtain tight control. Due to unmeasured disturbances, model errors, delay and other sources for imperfect control, back off must be introduced to avoid infeasibility dynamically. Back off results in a loss and should be as small as possible. Dynamic degrees of freedom, like buffer volumes, can be used to get a shorter loop from a manipulated variable to the bottleneck and hence tighter control and reduced back off. A buffer tank is a unit where the holdup (volume) is exploited to provide smoother operation (Faanes 2003). In this case we focus on flow-rate disturbances, where the disturbances are dampen by temporarily changing the volume (level variation). To illustrate the idea to include dynamic degrees of freedom in throughput maximization, an example with tanks in series is used.

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A Kalman filter tuning tool for use with model-based process control

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Abstract

Modern model predictive control schemes are based on discrete-time linear stochastic state-space models. They apply a Kalman filter to reconstruct the state from measurements and a Kalman predictor to predict the outputs. However, information about process noise and measurement noise statistics is required. Tuning the filter, i.e. choosing the values of the process and measurement noise covariances such that some performance index is optimized, is a challenging task. If performed manually in an ad hoc fashion it represents a considerable burden for the user. In addition, the process may be affected by unknown disturbances and identifying them requires skill and experience. Therefore there is a clear need for a tool that can perform filter tuning and disturbance identification or provide assistance to the user.

The filter tuning problem is essentially a covariance estimation problem where the Kalman filter gain is computed based on the estimated covariances. A promising technique for covariance estimation is the autocovariance least-squares (ALS) method proposed recently by Odelson and co-workers for linear time-invariant systems (Odelson et al., 2006). This method is based on the estimated autocovariance of the output innovations, which is used to compute a least-squares estimate of the noise covariance matrices. The approach has the advantage that routine operating data from the process can be used. The estimation problem can be stated in the form of a convex semidefinite program, which can be solved by interior-point methods which guarantee positive semidefiniteness of the covariance matrices. The estimation method has been generalized to systems with mutually correlated process noise and measurement noise.

The ALS method can also account for plant-model mismatch and unknown disturbances. This is done by augmenting the model with integrating white-noise dis-

turbances, which is a standard procedure for achieving offset-free control. Furthermore, the method can be used for identification of the disturbance structure (Rajamani and Rawlings, 2006). There are usually only a few independent disturbances affecting the process state and by introducing an additional objective the minimum number of disturbances can be identified by modifying the least-squares problem using regularization.

This Kalman filter tuning methodology is implemented into a software tool to facilitate practical applications. The tool for Kalman filter tuning is intended to be used in model-based control applications. The performance of the technique is demonstrated on systems controlled by model predictive control. Results from both numerical examples and a laboratory-scale multivariable process will be presented.

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Ensemble Kalman Filtering for state and parameter estimation in a reservoir model

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Keywords State estimation, Ensemble Kalman Filter, large scale models, reservoir models

Abstract The availability of a well tuned reservoir model is critically important for long term production planning to optimise the extraction of the hydrocarbon resources. Important decisions include the location of production and possibly injection wells, and the production rates on a well and field level. The problem is highly dynamic since production rates vary considerably during the lifetime of a field. Further, a large number of new wells are drilled, put into production and closed down during the same time span.

Reservoir models are usually implemented in ECLIPSE and can be very large. Models with several 100.000 states are not unusual. Production data and in some cases seismic data are available for updating the reservoir models.

First, the concept of the Ensemble Kalman Filter (EnKF) will be presented and compared to other Kalman filter options (linear Kalman Filter, Extended Kalman Filter and Unscented Kalman Filter). The comparison will emphasize challenges related to the use of Kalman filters on large scale models.

Second, the EnKF is applied to a somewhat simplified reservoir model, an ECLIPSE “shoebox” model with 2250 grid blocks containing oil and water. The model has two production wells and one water injection wells. The EnKF is compared to alternative ways of updating the reservoir model such us other Kalman Filter options and more conventional parameter estimation methods.

An outline of how the EnKF can be combined with Model Predictive Control (MPC) will be given at the end of the presentation.

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Session II.2: Controller and Control Structure Design

Dynamic Modeling and Control structure design for a Liquefied Natural Gas Process

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For transportation of natural gas (NG), pipeline transportation is often used. However, when gas volumes are moderate, and/or transportation distances are large, the capital and operating costs for pipeline transport become prohibitive. In such cases, transport of Liquefied Natural Gas (LNG) in tankers is often the preferred choice for bringing the gas to the market. It is quite common to have a heavy upfront investment in large industrial plants for producing liquefied natural gas (LNG) since cost per unit of gas volume will be relatively low over the plant lifetime. Multi-component refrigerants have been commonly used in such plant to achieve low temperature for LNG (-160 C at near atmospheric pressure).

However, there is a growing need for liquefaction of natural gas at places where it is not possible or economically acceptable to have a heavy investment. This includes local distribution of natural gas in small markets, where plant needs to be arranged at a gas pipe, while the LNG is transported by trucks and small ships. For such plants low investment costs have priority over optimal energy utilization. Traditionally the relative investment cost for small-scale LNG liquefaction plants increases almost exponentially with decreased production capacity from about 50,000 tones per annum and below[1]. SINTEF has developed a low capacity plant which requires low investment cost and is easy to construct at desired sites. The plant design has been patented by SINTEF [2]

This work is the continuation of the authors work [3] which has been acecpted for publication at American Control Conference(ACC) to be held in New York, US in July 2007. ACC paper discusses development of a dynamic mathematical model for this plant and design of a control structure for the plant to ensure stability and ease of operation. Fundamental limitations on performance of this plant are also analyzed.

However, heat exchanger model used in the above study neglects mass hold up of refrigerant in heat exchanger. Due to this assumption, in the developed plant model it is sufficient to control only liquid level in one of the flash drums. But it is known that approximately half of the refrigerant is not in drums and lies in the heat exchangers and in the pipe connecting different components in plant. So it is necessary to include this hold up in the model before a accurate control structure can be proposed and implemented. This work deals with modifying heat exchanger model to include refrigerant mass hold up in the heat exchanger and study the effect of this change on control strucuture design of the plant. A complete description of the process can be found at [2]. Here a brief process description is given. Fig 1 represents the simplified flow sheet of the SINTEF LNG plant. Some features of the process are removed for clarity. In Fig.1 sub-components of plants are numbered and referred as units. Units 13, 14, 15, 16, 17 and 18 are heat exchangers. Heat Exchanger (HX) numbered 13, 15 and 17 are called the 'Refrigerant HX' and HX number 14, 16 and 18 are called 'LNG HX'. Units 3 and 5 are separators and units 4, 6, 7, 8, 9 and 12 are valves. Units 10 and 11 are ejectors and units 1, 2 and 19 represent the condenser, cooling water stream, and the compressor, respectively.

The refrigerant is compressed in compressor (unit 19). After the compressor, the refrigerant is partly condensed primarily by water cooling in unit 1. The vapor from unit 3 is further cooled and partly condensed in unit 13 while the liquid from unit 3 is mixed with two refrigerant streams from unit 15 and 16. The vapor from unit 5 is further cooled and condensed in unit 15 and sub-cooled in unit 17 before it is flashed to a pressure of about 2-4 bar, giving the cold refrigerant for unit 17 and unit 18 before mixing it with the liquid from unit 5. After mixing, the refrigerant flow is divided and distributed to unit 15 and 16. The natural gas is cooled in unit 14, condensed in unit 16 and sub cooled in unit 18.

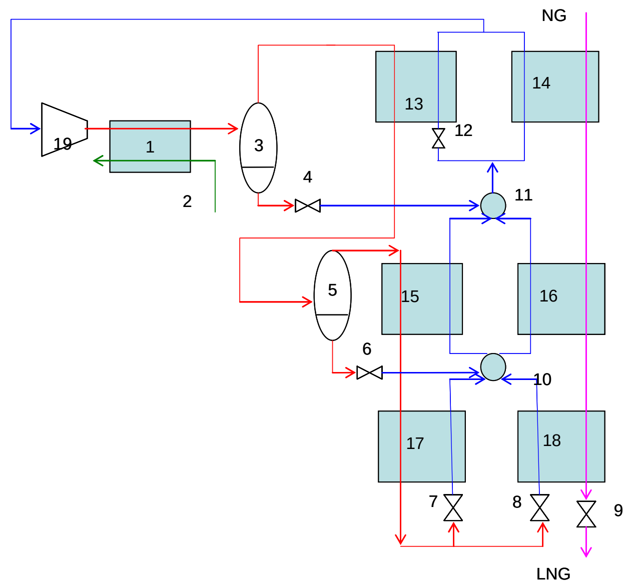

Fig 1: SINTEF Plant

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Abstract

Control Structure for Single Cell Protein Production in a U_Loop Reactor

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Bioreactor control has become very important since it may be difficult to control their non linear interactive behaviour. Originally bioreactor control was restricted to the regulation of abiotic variables such as pH and temperature to guarantee optimal conditions for the biological reaction or microbial growth. Nevertheless, biotic variables which potentially are subject to large fluctuations have a significant influence on reactor behavior, i.e., too much substrate can inhibit the microbial growth but too little can force an early stationary phase or the onset of endogenous decay.

A Single Cell Protein (SCP) production process carried out in a U-loop reactor (at DTU) is studied. This biological process is interesting since the microorganism is very sensitive to changes in the broth conditions where many factors can inhibit growth, thus a good control strategy can potentially enable optimizing bioprocess performance. In recent years, model based control has solved complex control problems in chemical processes. In particular, inventory control looks promising since it is a combined feedforward and feedback model based control which can be applied for non linear processes that require multivariable control structures. The presentation is divided in three main topics: modeling, control design and optimization.

Initially, a dynamic model for SCP production is formulated. The solution of partial differential equations for the axial dispersion model is approximated with a finite system of ordinary differential equations using a tanks in series model. The model is obtained by employing first principles for hydraulics of the system, heat and mass transfer phenomena, reaction kinetics, ionic interactions and overall balances for mass and energy. Making use of the formulated model, some open loop simulations are used to select an appropriate operating point and to propose a manual start-up procedure. Subsequently, the effect of model approximation accuracy is evaluated. An open loop dynamic behaviour analysis carried out to understand the system and identify the potential measurements and manipulated variables.

Using all the previous information the control objectives are formulated: to avoid the methanol inhibition at high and low concentrations, to avoid the oxygen inhibition at low concentrations and to provide the optimal values of temperature, pH and nitrate concentration in the cultivation broth.

Based on the control objectives and through employing the rules for categorizing control variables, a multilayer control structure is designed. At the end, methanol, nitrate and proton concentrations are controlled at the supervisory layer using inventory control. In the regulatory layer dissolved oxygen concentration is controlled making use of PI control and temperature using inventory control. Both centralized and decentralized inventory controllers are formulated to control the temperature and concentration of methanol, pH and nitrate in the reactor. These controllers are evaluated in different scenarios to analyze their performance including set-point

changes and disturbance rejection during steady state operation and start-up. PI control for dissolved oxygen concentration is included. Making use of the formulated control structure, the best operating set-point for methanol and dissolved oxygen are determined to maximize biomass productivity. Finally, the proportional inventory performance is improved including integral action in the control law, such that the controller can reject static model inaccuracies.

FLATNESS AND STEADY-STATE CONTROL DESIGN

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Extended Abstract. Control design based on the property of flatness has its origin in the works of the group of Michel Fliess and co-workers, see a seminal paper on flatness [1]. For continuous-time systems differential flatness is defined as follows. The system

$$\frac{dx}{dt} = f(x,u); \quad x(t) \in \mathbb{R}^n, \quad u(t) \in \mathbb{R}^m \tag{1}$$

$$y = h(x,u); \quad y(t) \in \mathbb{R}^l \tag{2}$$

is called differentially flat if there exists algebraic functions $\mathcal{A}$, $\mathcal{B}$, $\mathcal{C}$, and finite integers α, β, and γ such that for any pair (x,u) of inputs and controls, satisfying the dynamics (1), there exists a function z (of the same dimension as the control u), called a flat (or linearizing) output, such that

$$\begin{aligned} x(t) &= \mathcal{A}(z, \dot{z}, \ldots, z^{(\alpha)}) \\ u(t) &= \mathcal{B}(z, \dot{z}, \ldots, z^{(\beta)}) \\ z(t) &= \mathcal{C}(x, u, \dot{u}, \ldots, u^{(\gamma)}). \end{aligned} \tag{3}$$

When constructing open-loop controls for the state variable system (1) flatness of the system in the above sense facilitates the design. Then the control u and the state variable x are parametrized by the external function; the flat output z. Then the input-state pairs (u,x) (and the output y) can be obtained as functions of the parameter function z without solving of the original nonlinear ODE system. By a suitable choice of the parameter function one can drive the state of the system from one steady-state to another in a given finite time. A feasible parameter function in the scalar case is the following

$$z(t) = \begin{cases} z_0\,, & t < t_0 \\ z_r(t)\,, & t_0 \le t \le t_1 \\ z_1\,, & t_1 < t \end{cases} \tag{4}$$

where z_0 and z_1 are constant set points, and z_r is a function joining smoothly the two set points. To obtain a smooth control u one has to choose z_r sufficiently differentiable according to Eq.(3).

A certain class of controllability, or feedback-linearizability is a necessary condition in succeeding in this finite-time steady-state control. This flatness concept works also in discrete-time systems, see a development in the linear case [2]. Extensions to distributed-parameter systems described by linear or linearizable partial differential equations are studied in [3] and [4].

In linear continuous-time single-input single-output systems described in the transfer function (or polynomial operator) formalism, *i.e.*

$$A(p)y(t) = B(p)u(t)\,; \quad p = \frac{d}{dt}, \tag{5}$$

where $A(p)$ and $B(p)$ are polynomials of the derivative operator p, we can apply Bezout's theorem: If the polynomials $A(p)$ and $B(p)$ have no common polynomial factors then there exist polynomials $P(p)$ ja $Q(p)$ such that

$$P(p)A(p) + Q(p)B(p) = 1. \tag{6}$$

By using of these polynomials we obtain the equations

$$\begin{cases} u(t) = A(p)z(t) \\ y(t) = B(p)z(t) \\ z(t) = Q(p)y(t) + P(p)u(t) \end{cases} \tag{7}$$

which correspond to the equations (3).

In [2]ENSMP mechanical poorly damped systems have been built to demonstrate the effectiveness of flatness-based control. Control design for the demonstration systems are based on linear and nonlinear mechanical models and theory-fragments given above. In the presentation some video clips on the controlled systems with and without flatness design are presented.

Acknowledgement. This study is supported in part by European Union's 6th Framework Programme on Research, Technological Development and Demonstration in Marie Curie programme's Transfer of Knowledge project No: MTKD-CT-2004-509223 *Parametrization in the Control of Dynamic Systems (PARAMCOSYS).*

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CONTROL STRUCTURE SELECTION FOR THE DEETHANIZER COLUMN FROM MONGSTAD/STATOIL

Eduardo Shigueo Hori, Sigurd Skogestad

1. INTRODUCTION

The selection of a good control structure for a distillation column is important for the plant operation. In this work, it is studied the control structure selection of a deethanizer from Statoil/Norway. The objective is to separate ethane (C_2) from propane (C_3). This is a multicomponent column with a partial condenser and vapor distillate flow. The feed composition is (% mol): 2.1% of C_2, 59.8% of C_3, 12.5% of $i - C_4$, 25% of $n - C_4$, and 0.6% of $n - C_5$. The feed flowrate is 150 ton/h. The column has 36 trays and is fed in tray 26. The distillate flowrate is used, in the real plant, to control the pressure. As the feed is already very low concentrated in ethane, the distillate flowrate is very small (around 1% of the feed). Although this could cause some difficulties for pressure control, the results show that this is not a big problem if we also close a temperature loop. The simulations are done in ASPEN Plus and ASPEN Dynamics. The main objective is to find a structure that minimizes the effect of disturbances and implementation error (noise and bias) in top and bottom compositions (indirect control). The results show that it is better to control temperatures in the top section where the gains are higher and, as this is a multicomponent column, the two-point temperature control does not improve the control system performance (Hori and Skogestad, 2007*b*).

2. STEADY-STATE SIMULATION

The steady-state simulation was done in ASPEN Plus. Fig. 1 shows that the temperature profile is very flat in the bottom section. It implies that the temperature slope (temperature difference between neighbouring stages) is very small, so we shouldn't control a temperature in

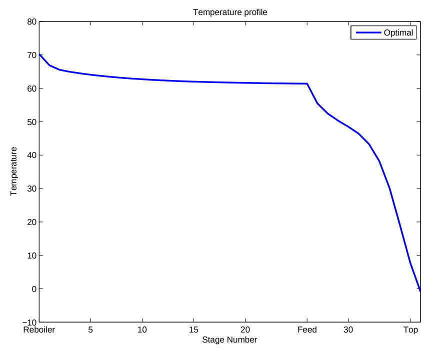

Fig. 1. Temperature profile.

this region (Luyben, 2005). This happens because the initial (high frequency) gain, which corresponds to the desired closed-loop time constant (Skogestad, 1997), is directly proportional to the temperature difference. For dynamic control purpose it is better to have a large dynamic gain, i.e. to control temperature at a stage where the slope is large.

3. DYNAMIC SIMULATIONS

The control structure used by Statoil is shown by Fig. 2, where the control loops used for pressure and level control are:

- control bottom level by bottom flowrate
- control pressure by distillate flowrate
- control reflux drum level by reflux flowrate

The two degrees of freedom available (condenser (Q_c) and reboiler (Q_b) duty) are used for temperature control:

- TIC198/T36: use Q_c to control top temperature
- TIC194/T4: manipulate Q_b to control temperature in tray 4
- TIC194/T36: manipulate Q_b to control temperature in the most sensitive tray

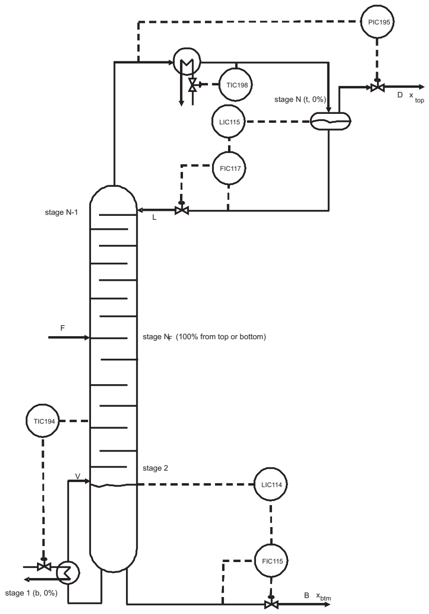

Fig. 2. Control structure used by Statoil.

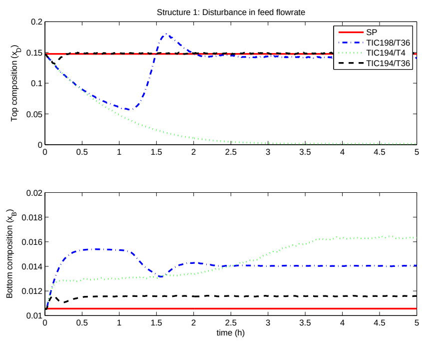

Fig. 3. Composition response.

Two-point temperature control was not included because its response was too poor. By the same reason, we excluded the open loop approach (keeping both temperature loops opened). Temperatures in trays 4 and 36 were chosen because they are controlled in the normal operation of the column.

To choose the most sensitive tray, we applied a step change in Q_b, showing that tray 36 has the highest gain (most sensitive). It means that we should control the temperature of this tray (Hori and Skogestad, 2007*a*). This result confirms that we shouldn't control a temperature where we have small temperature slope (temperature change from tray to tray), i.e., where the temperature profile is flat (Luyben, 2005).

The control structures are compared in Figure 3 for a disturbance in feed flowrate. In this plot, we compare the indirect control of the top and bottom compositions. The objective is to choose the control structure that gives the smallest composition deviation. It is possible to see that the best structure is TIC194/T36, which gives almost zero deviation for top composition and the smallest for bottom composition. This result confirms

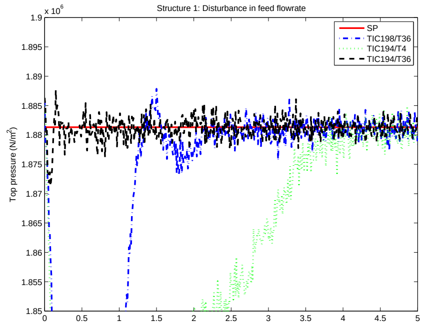

Fig. 4. Pressure control.

that it is better to control a temperature in the top section (highest gain and large temperature slope). Although it can seem a bit strange to control a temperature in the top section manipulating the reboiler duty, Hori and Skogestad (2007*b*) present some examples of columns that have this same characteristic. Fig. 4 shows that the pressure control is not a problem structure TIC194/T36, confirming that D can used for pressure control if we close a temperature loop.

4. CONCLUSIONS

The control structure selection of the deethanizer from Mongstad/Statoil was studied in this work. The results are similar to the ones presented in this paper and mostly confirm the findings from Hori and Skogestad (2007*b*). We shouldn't control a temperature in the bottom section because its trays are quite insensitive to the manipulated variables. This also confirms that we shouldn't control a temperature where the temperature slope is small. The control of pressure is not a big problem for this column if we have the right control structure because the temperature loop changes completely the dynamics of the column, invalidating the heuristics that we shouldn't use a small flow to stabilize the column.

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Control Structure Design for Biological Wastewater Treatment Plants

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Abstract

Environmental standards are becoming increasingly strict, due to raising public awarness for water resource protection. Hence, the necessity of efficient and reliable Waste Water Treatment Plants (WWTPs) becomes a mandatory task that have to face an important challenge arising from both regulation fulfillment and cost aspect of plant operation; as a conseguence, most of the existing plants have to undertake major upgrading, particularly for nutrient removals. In addition to plant improvements attained through the adoption of new equipment technologies, the application of careful considerations on control systems is required to achieve the improved benefits in practice. In particular, since inside a biological WWTP, the Activated Sludge Process (ASP) is the most common used technology to remove organic pollutant and nutrients from wastewater, we focus our attention on this process.

Automatic control of the activated sludge plant is rather sparse due to a variety of reasons. Lack of enforcement on effluent qualities, insufficiency of realiable sensors and the operation-related difficulties of applying process control due to poor understanding of process behavior are often cited as the main reasons. Nevertheless, mainly because the WWTP is still considered as a non-productive plant there is no real economic incentive of treating the wastewater. For this reason, an approach that preferably takes into account the economic expenses in the plant as well as the optimal operability of the process itself has to be prefered. In fact we can observe that the proper operation in the ASP process is translated into a constrained optimization problem. In order to run a WWTP economically, costs such as pumping energy and aeration energy should be minimized; nevertheless, the discharge concentrations to recipients should be kept at acceptable level.

It can be shown that optimal operation can be achieved in practice by designing the control structure appropriately. Controlled variables are the important link between layers in the hierarchic control structure and there are many issue involved. First, we should control the active constraints (which are optimal from an economic point of view in terms of minimizing the cost). Second, we need to find controlled variables associated with the unconstrained degrees of freedom. This is the issue of self-optimizing control. We are looking for the controlled variables for the ASP which when kept constant, indirectly achieve optimal operation in spite of disturbances. In order to trade them off against each other in a systematic manner we follow the control structure design proposed in [1].

In this presentation, the self-optimizing procedure is applied to the different activated sludge processes and it is shown how with simple considerations on the control structure the optimal operation can be achieved in the wastewater treatment plant. In its classical configuration an ASP consists of a bioreactor where in anoxic environment denitrification reactions take place and where in aerobic conditions, nitrification reactions occur. To maintain the microbiological population, the sludge from the settler is recirculated into the anoxic basin, while the sludge concentration is kept constant by means of sludge withdrawn from the settler. The bioreactor is represented by means of the Activated Sludge Model No. 1 [2], while the secondary settler representation is obtained with the Takàcs model [3]; these models are coupled together in a Matlab/Simulink environment.

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QUANTITATIVE FEEDBACK THEORY USED ON A TANK REACTOR MODEL

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EXTENDED ABSTRACT

An exothermic reaction is a highly nonlinear and locally unstable process. Thus, efficient control is necessary and nontrivial. Here, a first order, $A \rightarrow B$, exothermic reaction is studied in an ideally stirred tank reactor operating continuously, i.e. the reactor has an inflow and an outlet. Since the reaction is exothermic, a cooler is used for temperature control of the reactor. The cooling system is built up by tubes, situated inside the reaction vessel. In (Olesen *et al.*, 2007) a nonlinear model of this process is formulated and linearized in a number of operating points. These linearized models have great variations in parameters, for example some models are stable, while others have one or two unstable eigenvalues, reflecting the local instability of the original nonlinear model. Nevertheless, it would be desirable to have the same control strategy for most operating conditions of the tank reactor system.

Different control strategies for similar tank reactor models can be found in many publications. See for example (Henson and Seborg, 1997), (Morningred *et al.*, 1992), (Zhang and Guay, 2005) and (Lagerberg and Breitholtz, 1997). In all of these publications the tank reactor model is used as an example of a highly nonlinear system and the problems of a linear control strategy have bee pointed out.

The goal of this work has been to investigate the possibilities for finding a linear control strategy, where a small number of linear controllers are used to control the nonlinear system at a wide temperature interval. The method used for this investigation is quantitative feedback theory (QFT). QFT is a well established engineering design philosophy for uncertain feedback problems, see (Horowitz, 1993) and references therein. The QFT provides a method for finding linear controllers for uncertain processes or models. All possible variations in the model set define templates in the Nichols chart. The templates, a nominal arbitrary chosen model and closed loop specifications form Horowitz-Sidi bounds, used for loop-shaping the nominal model.

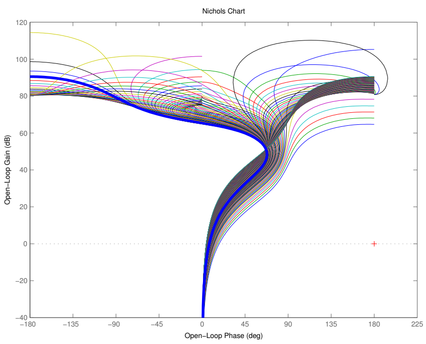

Fig. 1. The models linearized in operating points

Horowitz (1993) also present some methods for nonlinear system. One of these methods is to find equivalent linear models. Since linearized models, describing the tank reactor process near operating points are provided in (Olesen *et al.*, 2007), these linear models are used as linear approximations. Models linearized at temperatures between 300 K and 450 K are displayed in a Nichols chart in Figure 1, where the nominal model is indicated by a thicker curve.

As seen from the figure, the templates are will grow large for low frequencies. However for interesting frequencies, the templates are much smaller. The resulting Horowitz-Sidi bounds also show that one linear controller can be used to control all of the linearized models. However, the models linearized at operating

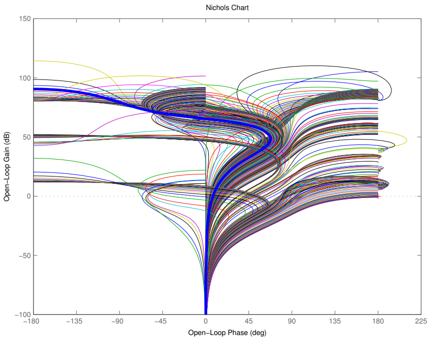

Fig. 2. Models linearized in operating points and in a number of other points

points only describe a small part of the nonlinear system. Therefore, in order to describe more of the nonlinear system, the model is also linearized in a number of non-steady-state points. This linearization results in an extra constant term, describing the values of the time derivatives of the state variables in the linearization point. This extra constant term is regarded as an input disturbance to the system. In Figure 2 the complex representations of these new linearized models are plotted in the same Nichols chart as the original linear models. From Figure 2 it can be seen that the templates are much bigger. In fact the resulting Horowitz-Sidi bounds are found to be very hard to fulfill. Even if a linear controller could be designed to fulfill all bounds, the performance would not be acceptable. However, if the models are divided into smaller temperature intervals, one linear controller can be found for each interval.

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Session III: Training Simulators

Competence development and knowledge transfer in an investment project in China. Case – start-up of a new and complex paper production line process

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Abstract: Efficient business start-up of a complex manufacturing plant in emerging markets poses a huge challenge to competence and capability development as a part of technology transfer. An integrated concept for human resources, competence and capability development in technology transfer projects is proposed. Important part of the new concept are knowledge and best practise toolkits, which are based on modelling conceptual mastery and work process knowledge needed in complex production process. The concept was used and verified in paper machine investment project in China. The results at individual level revealed no significant differences in conceptual mastery and work process knowledge compared to similar projects carried out in Europe. As business result, a new world record in speed was done just eight month after start-up, which indicates good competence and capability development. While traditionally the focus in business start-ups has been in technology transfer, we argue that in the emerging markets like China knowledge transfer and -mobility are becoming new key success factors. The evidence suggests that in the future more research should be done in the area of mobilization of knowledge and best practice transfer.

On Training Simulators in the Chemical Process Industry

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ABSTRACT

Simulation in the chemical process industry is a valuable tool for improving the production economics and the safety of plants. In this paper we discuss simulators built for training operators in the refining industry. The experiences gained in building a simulator, which covers the main sections of a Residue Hydrocracking Unit, are the basis of the presentation. A short overview of the simulator structure, the automation system implementation, and the modelling principles is given. The simulator system consists of process models of all involved units and pieces of equipment, a process database, a full emulation of the automation of the process, operator stations, and a teacher's console.

The target has been high-fidelity simulation, such that it should give the operator the same feeling as with the real process. The requirements that this sets on simulators are discussed both from a modelling as well as from an operational point of view. The benefits of training simulators are discussed. The main objectives in training are normal operation, disturbance handling, start-up and shut-down, as well as handling emergency situations. The requirements that this sets on process data, modelling principles, and modelling accuracy are discussed.

The resulting system is large and complex reflecting the real process. The challenges in the process unit model part is to build models that cover the physico-chemical properties well enough while making real-time simulation possible. Special attention has to be paid to reactor and reaction modelling, as well as to the components used in the distillation column models. The amount of detail is mainly seen in the equipment around the unit-operations and in the automation part. The automation system consists of a Distributed Control System, a Safety Instrumented System, all necessary sequence operations, and an additional cutback system for bringing the process back to a safe state after process problems. The complexity and the degree of automation is unusually high. The training simulator system is a multi-machine environment, which set high requirements on the data-transfer between the different parts.

Further, the objectives set high expectations on the user interfaces both for the operators and the trainers. The technical aspects of the system architecture, the user interfaces, and the interfaces between different parts of the training system are reviewed. The correspondence of the resulting systems with the real processes is presented as well as operator responses about the usability of the systems.

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ABB Model Editor -- A framework for Modelica based on-line estimation and optimization

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An important part in many projects at ABB is mathematical modelling. A relatively new way of describing models is via an object oriented modeling language called Modelica.

Modelica

Modelica is developed especially for multi-domain systems. It could, for example, be a mix of thermodynamic, mechanical and electrical subsystems as in a fossil fuelled power plant. The idea is that there should be libraries consisting of process objects each represented by an icon, which then can be configured graphically to a model by drag and drop. Figure 1 shows a part of the model for the ore concentration plant at Boliden's zinc mine at Garpenberg, Sweden.

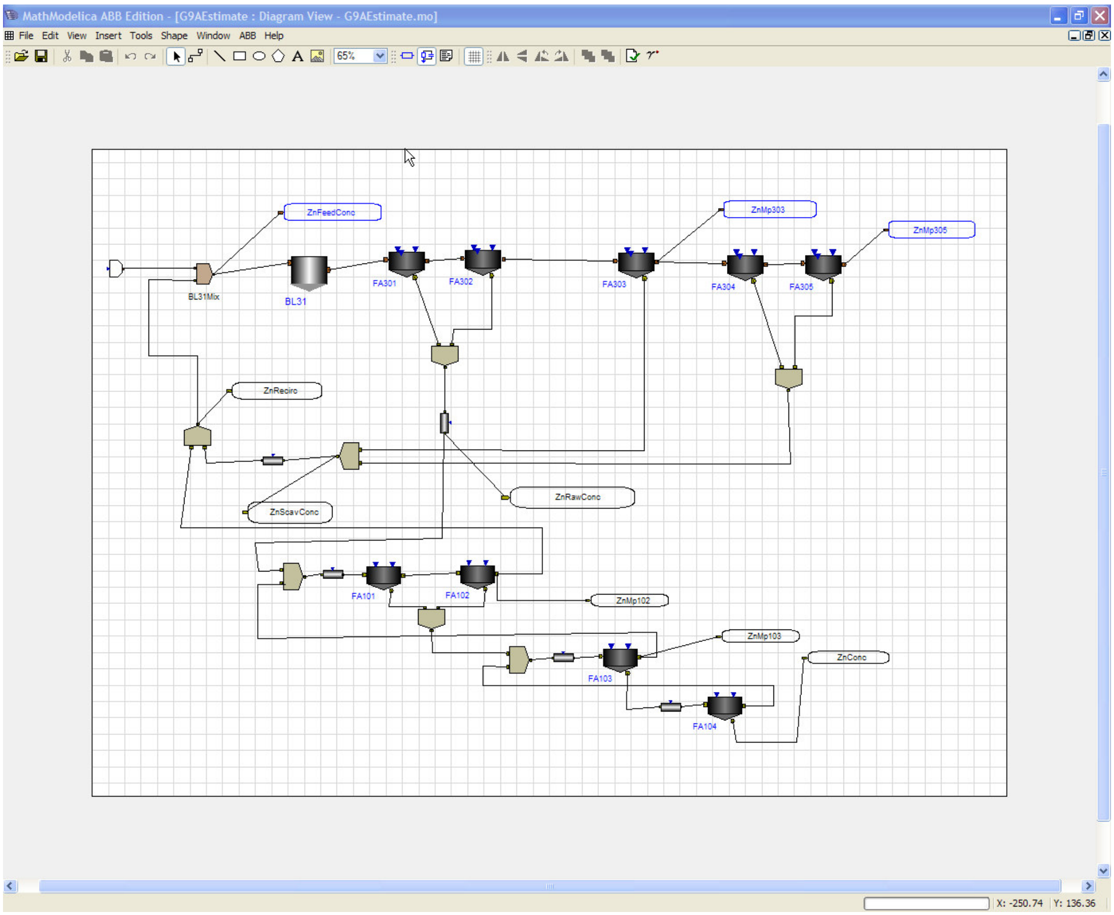

Figure 1. Model of zinc flotation

Modelling tools

Today there are two commercial tools for Modelica both Swedish: MathModelica from the Linköping based company MathCore Engineering AB and Dymola from Dynasim AB in Lund. However, Modelica is by no means only a Swedish thing. On the contrary, it starts to be have a clear international spread. For example one of Dynasim's major customers is Toyota. Modelica is indeed a standard which has been developed by the Modelica Association, see www.modelica.org.

An interesting activity is coordinated by the Computer Science department at Linköping University, namely the development of OpenModelica, which is a free simulation solver for Modelica.

Use within ABB

In recent years the use of Modelica within ABB has been rapidly increasing. We have had projects in such diverse areas as thickness control in cold rolling mills, simulation of pulp mills, and startup optimization of power plants. At the moment we have at least five different projects in as many different research centers world-wide using Modelica for various purposes.

On-line optimization

The original use of Modelica, supported by both MathModelica and Dymola, is for dynamic simulation. An ABB application becoming more and more common is to use the model as equality constraint in an optimization. The optimization solvers that we use then typically need the model equations in a subroutine. Furthermore, they often also want the first and second derivatives of the model equations. For this purpose we have together with MathCore developed an ABB Model Editor – or MathModelica ABB Edition 1.1 as the official name is– which is a complete MathModelica with an ABB specific part for code generation.

Towards Integration of Simulation in Engineering Work Processes

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Extended abstract for the 14th NPC Workshop 23-28-8-2007 in Espoo, Finland

Integration of modelling and simulation software to other engineering software has been an intended activity in focus for many years. Interoperability aspects have been touched both with regard to simulation-time connections and modelling-time connections. Control engineers have developed methods for identifying the dynamic performance of running plants but concurrent process and automation design of new plants has not reached its potential extensive application.

Excellent interfaces have been made for run-time operation of models interacting with hard-wired equipment as well as with digital control systems, for instance to test control systems of flying vehicles. Tailored connections to specific digital control systems have, however, required substantial efforts. De-facto standardisation efforts, such as initiated by the OPC foundation have notably remedied the situation.

Control system vendors have agreed on an open specification OPC for real time access to control system data. Further, this OLE for Process Control standard interface has recently been extended with strong Unified Architecture concepts, which open up new opportunities for on-line access to data according to plant semantics. Efficient simulation-time connections make it easier to test and optimize the functionality of interconnected processes and control systems, both in normal situations and in anticipated disturbances.

Modelling-time connections are expected to be a future key-issue in improving the efficiency of engineering work processes. The success is a matter of multifaceted awareness and readiness: Are the simulation tools ready to accept formal process information specifications as input data? Are there available catalogues of suitable digital information of separate process components and automation system elements? Are suitable integration standards available for specification of process structure and are they taken into use in common computer aided design and engineering software tools? Are the design engineers, the commissioning workforce, the operating personnel, or the management representatives ready to grab the opportunity offered by new computer aided working methods? Will new agile business undertakings grow up that are ready to supply the required services in a networked environment?

Tailored approaches to convey data calculated by design dimensioning tools to process design databases have been accomplished. The increasing amount of information that is generated, exchanged, shared, stored and retrieved during the engineering, design, installation, operations, maintenance and demolition of a process or power plant, known as the plant life cycle data, requires new standardised approaches. During all the phases of the plant life cycle different computer based tools are already used to assist us as human beings in manipulating and interpreting plant information. Still, however, PI-diagrams are manually re-drawn as input for simulation tools. The design parameters are re-typed. Errors are made. Work hours and calendar months are consumed.

The standardisation for required information management and the development of sufficient and reliable open source application software and require significant monetary funding and dedicated concerted actions to reach a mature readiness state. In principle the basic technologies are available. The answer of how to master the increasing amount of data and the number of networked computers that have to exchange, share, store, and retrieve all relevant information, is in a neutral language which has to be understood by all computer systems involved. We are not considering a computer programming language like the FORTRAN or Java but a specification language with artificial intelligence features. These thoughts were already introduced some years ago, in the beginning for separate components only. The concept was given the name STandard for Exchange of Product model data. It is the name for the International Standard Organization ISO 10303 series of standards. One part of STEP has been created to support the information needs in the design and engineering environment. This STEP part is Application Protocol 221 or AP221. Initially the scope of AP221 did only cover functional (engineering & design) data and schematic representation but due to increasing industrial needs it has been extended to cover the full process plant life cycle including e.g. materials and connections. For the latter purpose AP221 has been set-up as a very generic model allowing flexible (data-driven) definitions of e.g. equipment and material classes, activities and process functions. In other words the initial concept was extended in such a way that it is suitable now to describe a whole plant. The newly accepted interoperability standard, ISO 15926-7 originally developed for oil an gas industry needs further promotes integration, sharing, exchanging, and hand-over of lifetime information, applying the Semantic Web (with languages RDF, RDFS, OWL, SPARQL, SOAP, and XSLT).

Improved data integration is now formally made possible. It can be enabled by extensive harmonization of existing and new standards, also including other industrial domains than process industry. For architectural, engineering, construction and facilities management in building industries the International Alliance for Interoperability (IAI), has produced relevant standard data models: the Industry Foundation Classes (IFC). A large variety of computational tools have been developed making benefit of standardised specifications. The electromechanical industry has a long tradition of developing and applying standards authorized by the International Electrotechnical Commission (IEC). Since 1993, there has been an international standard IEC 1131 for Programmable Logic Controllers (PLC). Section IEC 1131-3 in that standard specifies syntax, semantics and display for the formats known as ladder diagrams, sequential function charts, function block diagrams, structured text and instruction lists. Today many PLC suppliers and PLC tool providers conform to IEC 1131, and in many safety critical applications IEC 1131 is mandatory. A larger take up of this standard would facilitate the vendor independent modelling and simulation of control system functionality.

We are in a very interesting phase of the relevant developments. The computer hardware and software technology and the required the interoperability concepts are available for total plant data model integration. Road maps have been made unquestionably revealing the economical benefits that can be achieved. Now it is time to act. However, many different aspects of process automation are affected and have to be addressed before we can make the bigger steps required.

Experiences of dynamic process simulation in the pulp and paper industry: Four case studies

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This presentation gives a short account of some of the simulation activities at VTT in the pulp and paper industry. The presentation is restricted to dynamic process simulation. It should be noted that VTT offers a wide range of simulation and modelling expertise utilising for example steady-state simulation, multiphase thermodynamics and computational fluid dynamics.

The cases discussed are:
Case 1: Continuous pulp digester
The first case discusses further developments of the extended Purdue continuous digester model and its integration into a dynamic process simulation software. The objective of the work was to implement the model in such a way to the process simulation platform that would make it an easy-to-use part of a larger process model. In the work the Purdue model was extended with chip compaction and liquid and chip level calculations as well as with an alternative pulping reaction kinetics model, the so called Gustafson kinetics. The model was validated by comparing its outputs to the results presented by Wisnewski et al. in 1997. Application of the simulation model to an actual pulping process ranging from the chip silo to the blow line is presented.

Case 2: Board machine grade change simulator
The second case describes a study in which a dynamic simulation model of a 3-layer board machine was developed. The simulation model consists of stock preparation and proportioning, short circulations, wire and press sections, and drying section including the steam and condensate systems. Physical, first principles models were used whenever possible. The control system and automatic grade change program were modelled as well. The simulator was extensively validated against measurements. A simulation case concerning grade changes is discussed: the re-tuning of the automatic grade change program.

Case 3: Paper machine stability studies
The third case presents a study in which the objective was to find out differences between the studied paper machine processes and to evaluate how the differences affect process stability. More precisely periodic disturbances and their attenuation in the processes were examined in this study. Two modern newsprint paper machines were analysed and simulation models based on first principles were constructed with APROS® Paper simulation software. The study included an experimental part where laboratory and tracer measurements were used for identification of process behaviour. The simulation part included modelling of both wet end systems and their disturbance analyses.

Case 4: Pulping process improvement
The last case present results of modeling and simulation studies at a Finnish CTMP-mill (chemi-thermomechanical pulp). The aim of the study was in improving the quality of the screened pulp and in overall improvement of the screen room's runnability. Simulation, in addition to other advanced mathematical methods, was used as a tool in this. The simulation model presented in this paper is a combination of dynamic mechanistic conservation laws and empirical pulp quality models. The quality models integrated to the Apros® Paper simulator were screen freeness (CSF) and screen shive fractionation models. Also the changes in freeness and in pulp fiber length distribution were modeled for the reject refiner. These quality models were based on several mill trials. The integrated process model was validated with logged process measurement data. The data included all the DCS position in the CTMP-mill, including new on-line pulp quality measurements.

Game play in Engineering Education – Concept and Experimental Results

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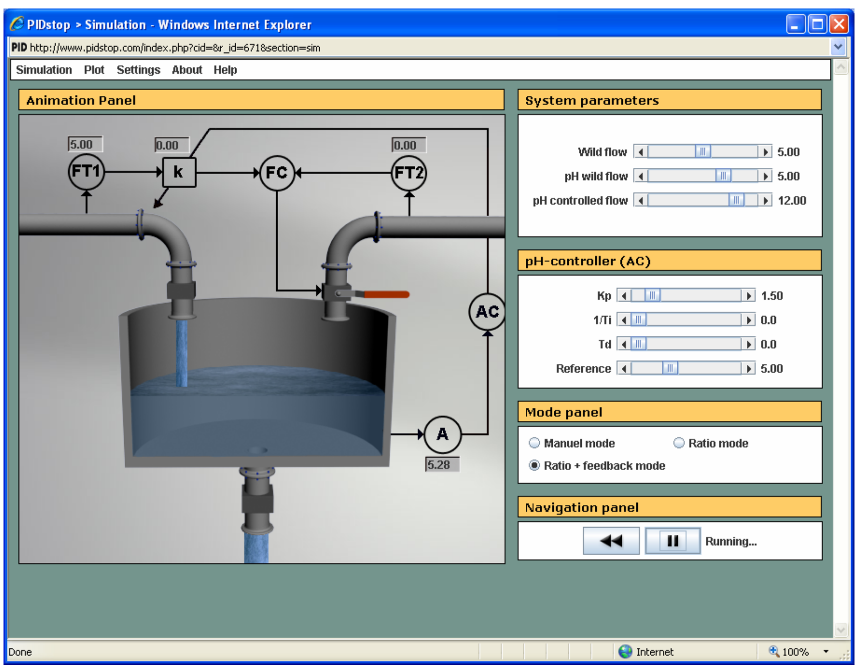
Keywords Dynamic simulation, games, engineering education, e-learning, user feedback

Abstract Dynamic simulators combined with educational games may create a new and improved learning culture by drawing advantage of the new knowledge and skills of today's students obtained from extensive use of interactive computer games. We present a design basis and a set of online learning resources based on dynamic simulators and taking advantage of game-related features. The e-learning resources are used in basic engineering courses. Feedback from approximately 3000 engineering students will be presented, the main conclusion being that students clearly view game-related learning resources as having a positive learning effect.



In this paper online learning resources focussing on process control will be emphasized. An example is shown in the adjecent figure. The resources have been developed and tested in cooperation with partners in Spain, Romania, Germany and Switzerland during within the framework the EU-sponsored Autotech project.

The prototype system used to develop and harbour the online learning resources is PIDstop. The name arises from a merger of the terms "pitstop" and "PID-control". Pitstop a place to fuel or more generally perform maintenance of a racing car, the analogy in our context is "tanking up knowledge". Learning resources from PIDstop can be integrated into any modern Learning Management System. The system is implemented using HTML/CSS, powered by a PHP server for dynamic content and MySQL database for storing user data. The dynamic simulations and games are implemented using Java

Applets meaning that PIDstop learning resources are available to anyone with a Java-enabled browser.

Session IV.1: Modelling and Identification

Comparison of Experimental Designs for Identification of Ill-Conditioned Systems

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Essentially all industrial systems are multivariable in the sense that there are several outputs, which we may want to control, and several inputs by which the outputs can be affected. Usually every input in such a multiple-input, multiple-output (MIMO) system affects more than one output. As a consequence of this, there are usually combinations of inputs that have a stronger effect on the outputs than other combinations of equal magnitude. If this effect is considerable, the system is "ill-conditioned" and it is characterized by a strong "gain directionality". A typical example of such a system is a distillation column.

The directionality properties of ill-conditioned MIMO systems make the identification task much harder than for single-input single-output systems. It is now well known that a proper identification requires that the various directions are excited by the inputs. It is easy to obtain information about the direction(s) with the highest gain(s), but in order to obtain information about the properties in the low-gain direction(s), it is important to explicitly excite the latter sufficiently and in such a way that directions with higher gains are suppressed. Generally, this requires that all inputs are perturbed simultaneously and that they are *correlated* in certain ways. Furthermore, the strength of the excitation in the various directions should be inversely proportional to the gain in the respective directions. The experiment design is thus crucial for a successful identification.

Häggblom and Böling (1998) have verified the importance of these principles in the identification of a pilot-scale distillation column using series of step changes as excitation signals. They found that identification experiments where each input was excited one at a time resulted in models that predicted the low-gain behaviour poorly and were not well suited for controller design. In the present work, we investigate experimentally if the directionality problem can be alleviated by the use of a more sophisticated excitation signal than a step change. We use Pseudo Random Binary Sequences (PRBS) as an example of such a signal.

When PRBS signals are used for identification of MIMO systems, current practice is to excite each input one at a time or to excite all inputs simultaneously with uncorrelated PRBS signals. We investigate these methods using various PRBS designs. Because these approaches do not follow the identification principles laid out above, we also study ways of applying PRBS signals simultaneously to all inputs so that the desired correlation and excitation strength is obtained. We consider several ways of doing this. One is to excite the various directions one at a time, another to excite all directions simultaneously in an uncorrelated way (note that we are here speaking of gain directions, not individual inputs). In the design of the PRBS signals, we can in both cases take into account the fact that changes in the low-gain direction tend to be significantly faster than changes in the high-gain direction in distillation columns.

The main conclusion of this study is that the use of PRBS signals in the identification of an ill-conditioned system does not necessarily give a better model than step signals. For both types of signals, it is crucial that the various gain directions are properly excited.

Straightforward Identification of Continuous-Time Process Models from Non-Uniformly Sampled Data

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1 Introduction

Approaching parameter estimation from the discrete time domain has been the dominating paradigm in system identification. Identification of continuous-time models on the other hand is motivated by the fact that modeling of physical systems often take place in the continuous-time domain. In many practical applications there is also a genuine interest in the physical parameters.

Parameter identification of continuous-time systems is an important subject of its own. See for example the monograph by Sinha and Rao [5]. Recently there has been a renewed interest in continuous-time system identification in general and continuous-time noise models in particular, [4],[3],[2],[6], [1]. At the IFAC World Congress in Prague in 2005 there were two sessions alone devoted to this particular subject.

The objective of the presentation at the Nordic Process Control Workshop will be to show how one can identify continuous-time input-output and time-series models from data that is non-uniformly sampled. This is a scenario which is particularly important in the process industry, since data is often stored at non-equidistant time instances in order to reduce storage volumes.

The presentation will be divided into two parts. Firstly, it will be shown that for input-output models the intuitive answer is that one should use polynomial spline functions in order to reconstruct the data on a uniform time grid. Then, standard methods for continuous-time identification should be used. If the relative degreee ℓ of the continuous-time system is assumed to be known, a spline function of order $\ell + 1$ is the correct choice.

For time-series models in continuous-time, the answer comes as a surprise. One would think that here too, spline interpolation back to a uniform grid would be the correct answer. This is however not the case, and it can be proved mathematically that such an approach would yield erroneous results. Instead, simple use of the Kalman filter provides a means of reconstructing the time-series on an uniformly spaced time grid using only past data.

2 Continuous-Time Input-Output Models

Consider the setup in Figure 1, consisting of a zero-order hold circuit H at the input, a continuous-time system G_c and a sampling circuit at the output Here G_c is represented by the transfer function

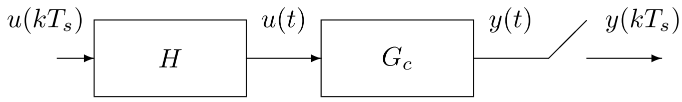

Fig. 1. Input and sampling setup for a continuous-time system.

$$G_c(s) = \frac{b_0 s^m + b_1 s^{m-1} + \cdots + b_m}{s^n + a_1 s^{n-1} + a_2 s^{n-2} + \cdots + a_n} \qquad (1)$$

where $\ell = n - m$ is the so called *relative degree.* If the continuous-time Fourier transforms of the output $Y_c(i\omega)$ and input $U_c(i\omega)$ were known at a frequency grid $\{\omega_k\}_{k=1}^{N_\omega}$, the parameters of G_c could be identified as

$$\hat{\theta} = \arg\min_{\theta} \sum_{k=1}^{N_\omega} |Y(i\omega_k) - G_c(i\omega_k, \theta) U_c(i\omega_k)|^2 \qquad (2)$$

where

$$U_c(i\omega_k) = H(i\omega_k) U_d(e^{i\omega_k T_s}). \qquad (3)$$

Here U_d is the discrete-time Fourier transform of the equidistantly measured input and H.

Unfortunately the inter-sample behavior of the output y(t) is not known. However, it is possible to estimate Y_c from Y_d as

$$\hat{Y}_c(i\omega) = F^c_{\ell+1,T_s}(i\omega)Y_d(e^{i\omega T_s}). \tag{4}$$

where

$$F^c_{\ell+1,T_s}(i\omega) = \frac{T_s\left(\frac{e^{i\omega T_s}-1}{i\omega T_s}\right)^{\ell+1}}{\frac{e^{i\omega T_s}\Pi_\ell(e^{i\omega T_s})}{\ell!}} \tag{5}$$

and $\Pi_\ell(z)$ are the Euler-Frobenius polynomials. This is equivalent to interpolating the data using polynomial splines of order $\ell+1$ with equidistant knots, such that

$$\hat{y}_c(t) = \sum_{k=-\infty}^{\infty} y(T_s k) f^c_{k,\ell+1,T_s}(t) \tag{6}$$

in the fundamental spline basis where the Fourier transform of $f^c_{k,\ell+1,T_s}(t)$ is $F^c_{\ell+1,T_s}(i\omega)$. The same line of reason carries over to the non-uniformly sampled case.

3 Time-Series Models in Continuous-Time

In this section we will consider continuous-time ARMA models represented as

$$y(t) = H_c(s)e(t) \tag{7}$$

where $e(t)$ is continuous-time white noise such that

$$Ee(t) = 0$$
$$Ee(t)e(s) = \sigma^2\delta(t-s)$$

and

$$H_c(s) = \frac{s^m + b_1 s^{m-1} + \cdots + b_m}{s^n + a_1 s^{n-1} + a_2 s^{n-2} + \cdots + a_n}. \tag{8}$$

Assume that we have sampled the output of the model (7) non-uniformly, such that

$$Y_n = \big(y(t_1),\ y(t_2), \ldots,\ y(t_{N_t})\big)^T \sim \mathcal{N}(0, R_n) \tag{9}$$

where R_n is a multivariate covariance matrix. We wish to reconstruct a new vector

$$Y_r = \big(y_r(T_s),\ y_r(2T_s), \ldots,\ y_r(N_t T_s)\big)^T \tag{10}$$

with the same statistical properties as the uniformly sampled output

$$Y_u = \big(y(T_s), \ldots,\ y(N_t T_s)\big)^T \sim \mathcal{N}(0, R_n). \tag{11}$$

If this is performed by a scalar operation on the non-uniformly sampled output such that

$$Y_r = SY_n, \tag{12}$$

the $N_t \times N_t$ matrix S must satisfy the equation

$$SR_nS^T = R_u. \tag{13}$$

It can be shown that $Y_r = SY_n$ is equivalent to running the non-uniformly sampled data Y_n through a Kalman filter and compute the innovations sequence. The innovations are scaled to produce a new "uniformly sampled set of innovations". These can then be fed into the innovations form of another Kalman filter which yields the reconstructed data Y_r. The computational complexity of this process is linear in the number of datapoints N_t.

The Kalman filters above relies on the true system parameters which are not known in advance, but approximations which relies on the relative degree $\ell = n - m$ of the system can be used with success. Standard methods in either the time or frequency domain can then be used to estimate the parameters of the time series model in (7).

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Jonas Gillberg was born 1975 in Vänersborg, Sweden. He received his Bachelor of Science degree in Business Administration and Master of Science degree in Electrical Engineering in 2000, both at Linköping University. During 2001 he worked as a management consultant at the Andersen Consulting Stockholm Office. In 2002 he joined the Automatic Control group at Linköping University. He was awarded the Doctor of Philosophy degree in Automatic Control in 2006 under the supervision of Prof. Lennart Ljung. He is currently working for Preem Petroleum AB.

Identification of uncertain systems using support vector regression and orthogonal filter expansion

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April 14, 2007

Abstract

Support vector machines have been introduced as a powerful approach to classification and regression problems. Support vector regression is based on Vapnik's ϵ-insensitive loss function and structural risk minimization, which aims to bound the mean approximation error when the model is determined from a finite data set. Support vector regression has several appealing properties for black-box identification. The solution is defined in terms of a convex quadratic minimization problem, for which convergence to the global solution can be guaranteed. Moreover, structural risk minimization introduces robust performance with respect to new data. Support vector methods have been applied successfully to system identification problems, including linear ARX models, nonlinear dynamical models, partially linear models and Hammerstein models.

In this contribution support vector regression is applied to identify linear uncertain systems. The system transfer function is expanded in terms of a class of orthogonal filters, such as Laguerre or Kautz filters. Support vector regression is applied to determine a nominal model and an uncertainty set which is not invalidated by the data. One feature of using orthogonal filter expansions in system identification is that the order of the identified model may be high, even when a low-order model which achieves the same accuracy may exist. In order to obtain a low-order model, model reduction can be applied to the initially identified high-order model. An identified model which can be more accurately approximated by a low-order model is obtained by introducing smoothness priors using a weighting of the variations of the frequency response in the support vector procedure.

Dynamic modelling and simulation to overcome the initialization problem in steady state simulations of distillation columns

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Background

Modelling of chemical processes is today the foundation to almost any operation including design, control, planning, retrofitting. As varied as the use of models is its structure: models are built for a particular purpose, to meet the requirement of the application.

Though there is obviously a need for dynamic models, at least in chemical engineering the most common models are steady-state models mainly used in designing and retrofitting, but also in some control and planning applications. With distillation being the most common separation unit, its models have been subject of studies for decades. The computation of steady-state distillation models is a notorious problem as it consists of a large number of equations which proliferates mainly with the number of components and number of trays. Solving such a model implies to solve this large-scale algebraic problem for a single set of roots representing the equilibrium state of the distillation. The numerical methods being used for this purpose have usually a very small convergence radius, which gave rise to a lot of research (Komatsu and Holland 1977, Holland 1981, Taylor et al. 1996, Rabeau et al. 1997, Grossmann et al. 2005). Thus whilst computing has improved tremendously, little progress has been made in solving the initialization problem.

Idea for approaching the initialisation problem

The authors' idea for approaching the initialisation problem is to use a dynamic description (Rademaker et al. 1975, Skogestad 1992) that mimics the behaviour of a distillation column close enough so as to simulate a dynamic path starting with a very simple generic initial state and integrating up to the desired operating condition. Thereafter one may switch to a steady state description of the plant and continue the computations, if so required.

Starting point

Earlier studies have shown that bringing two isolated phases into contact will converge monotonically to the steady-state under the condition that the heat transfer is significantly faster than the diffusional mass transfer through the phase boundary (Asbjørnsen 1973, Preisig 2004). This is taken as a starting point to suggest a sequence of physical operations which will guide the dynamic model to converge to the desired steady-state condition. Thus by switching from a steady-state simulation to a dynamic simulation one substitutes the complex initialisation problem by a simple one plus an integration over a feasible physical path. Mathematically this implies that one solves a set of Differential Algebraic Equations (DAE) instead of a large set of algebraic equations. With DAE solvers having advanced tremendously over the past decades, using a dynamic model may even be competitive to using a steady state model.

The model

The model is constructed from simple components: each tray, boiler and condenser are considered as a dynamic flash whereby each flash is contained in a fixed volume, tray volume, boiler volume and condenser volume respectively. Staking up such two-phase containments, the column becomes a tower of dynamic flash "drums". The transfer rates for mass and heat were chosen empirically so as to satisfy above-mentioned conditions. The internal streams are driven by the heat source and sink in the boiler and the condenser, respectively.

Step by step to the operating conditions

The procedure representing a feasible physical path leading to the desired steady state starts with a set of isolated containments forming pairs of gas and liquid both in isolation. Those are first brought in contact with each other, pair by pair thereby fixing the respective joint volume to represent the volume of the boiler, each stage and condenser, respectively. The individual phases are initialised within the domain of operation. Since a priori the two phases are not in equilibrium, they can exchange energy (in the form of heat and volumetric work) and mass both being diffusional processes through the common phase boundary. The conductive heat stream, driven by the different temperatures of liquid and gas phase, is significantly faster than the mass diffusion, which makes the temperatures in the two phases to converge quickly.

The mass exchange driven by the chemical potentials, accordingly to fundamental transfer laws, is slower. The mass stream induces also convective energy transfer as mass carries internal energy.

The heat transfer in the liquid phase is assumed to be very fast (event dynamics). This makes the temperature on the boundary identical to the liquid bulk temperature. The energy associated with the phase change is thus solely associated with the liquid phase. This simplifies also the computations as otherwise one has to compute the conditions on each phase boundary, which involves solving for roots of a set of algebraic equations (dimension: number of components + 1 for each boundary). The first step is completed when the two phases in each part of the column have reached an equilibrium.

Then it is time for the second step: adjusting the liquid levels. If the liquid level is too little, meaning the fluid does not reach up to the weir height on each stage, liquid is added on the top with the overflows modelled with the weir equation. In case there is too much fluid, one may have to drain some out of the boiler so as to adjust the overall hold-up.

With the next step energy is drawn in form of heat from the liquid phase of the condenser driven by the difference between the temperature of the liquid phase and the temperature of a cold reservoir. This procedure excludes anything like drop or film formation.

Up to this point the gas phases are not connected. Only at this point this communication of mass driven by the pressure difference is enabled. The transfer model consists of two parts, namely a resistance in the construction, the dry tray resistance, and the hydraulic pressure drop on the tray.

Finally heat is supplied to the liquid phase of the boiler driven by the difference in temperature between a warm reservoir and the liquid phase excluding any bubble formation.

The complete model consists for each stage of number of components mass balances for the gas phase and the liquid phase, and an energy balance for each liquid and gas phase.

Advantages of the approach

The approach was found to be extremely robust. Different initial conditions were tested. Some conditions lead initially to an inverted pressure profile, that is, the pressure on the top was higher than the pressure in the boiler. Adjusting the liquid levels on the trays did not have a large effect on the pressure distribution. The pressure though changed drastically as cooling and heating was enabled. In all cases, the column converted to the correct pressure profile thereby going through a complicated inversion process for the pressure as well as the temperatures converging monotonically towards the final profile during the last phase.

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Dynamic modelling of resin catalyst swelling during oxygenate reactor startup

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Acidic ion-exchange resins are widely used as catalysts in large-scale production of fuel oxygenates like MTBE, ETBE, and TAME. These resins have a strong tendency to absorb polar compounds such as water and alcohols. This causes significant swelling of resin particles, which, in turn, determines the volume of packed bed. Typically ion-exchange resins are delivered as wet. During reactor startup water must be removed from resin. This can be a slow process, because water has low solubility to hydrocarbons. Water solubility can be improved and its removal rate from the reactor can be accelerated by adding alcohols to the reactor feed. Detailed understanding of resin swelling and water removal dynamics is essentially important for the safe and fast reactor start-up.

In this work, a detailed phenomenological model is developed to investigate oxygenate reactor dynamics. Resin and continuous liquid are described in the model as separate phases. The bed is divided into ideally mixed, connected subregions to describe radial and axial temperature, concentration and swelling profiles in the reactor. Subregion volumes are allowed to change depending on the degree of swelling. Superficial liquid flow profiles in the bed are solved from momentum balances with Ergun friction terms. Radial dispersion of mass and heat are calculated from the literature correlations. Conductive heat transfer in both radial and axial direction of bed is taken into account.

Local diffusion and swelling phenomena in resin particle are described based on Maxwell-Stefan multicomponent diffusion theory. Reaction rates are related to local concentrations inside resin to analyse complicated coupling between reactions, heat and mass transfer. Resin-liquid equilibrium at the surface of resin particle is calculated from the Flory-Huggins activity model by taking into account resin-solvent interactions and elastic pressure of resin matrix. During reactor startup two liquid phases can be formed in the continuous liquid phase. This is described based on an efficient liquid-liquid flash algorithm. Flory-Huggins interaction parameters are obtained by fitting against resin-liquid equilibrium and swelling measurements. Solvent-solvent interaction parameters are determined from experimental vapour-liquid or liquid-liquid equilibrium data when available, otherwise from UNIFAC-predictions.

A multifunctional laboratory scale equipment presented in Figure 1 was built to validate the developed model. Transparent tube of 40 mL volume was filled with catalyst. The reactor was operated under high pressure and temperature (17 bar and from 80 to 100°C). Mixture of light hydrocarbons (C_4) and oxygenates was introduced into the reactor with constant flow rate with syringe pumps (GA_1, GA_2). The feeds were mixed inside the temperate controlled oven, reacted and flowed further to the analyzing equipment. Finally, the flow was collected into a product container.

Effects of temperature, flow rate and content of tert-butyl alcohol and water on reaction rates were investigated. The product flow was analyzed in-line with automated gas chromatograph (FID detector) and NIR. Swelling and shrinking of catalyst were photographed. Water content in the catalyst was determined with Karl Fischer titration before and after experiments.

Preliminary simulations by using the developed reactor model indicate that resin particle swelling depends strongly on local concentrations of alcohol and water, which are adsorbed strongly to the resin. Spatial variations of temperature and concentrations in the bed are significant. The simulation results agree qualitatively with the experiments. The next step will be quantitative model validation against laboratory experiments. After this, the model will be a useful tool for the investigation of oxygenate reactor dynamics and for the development of accurate control systems.

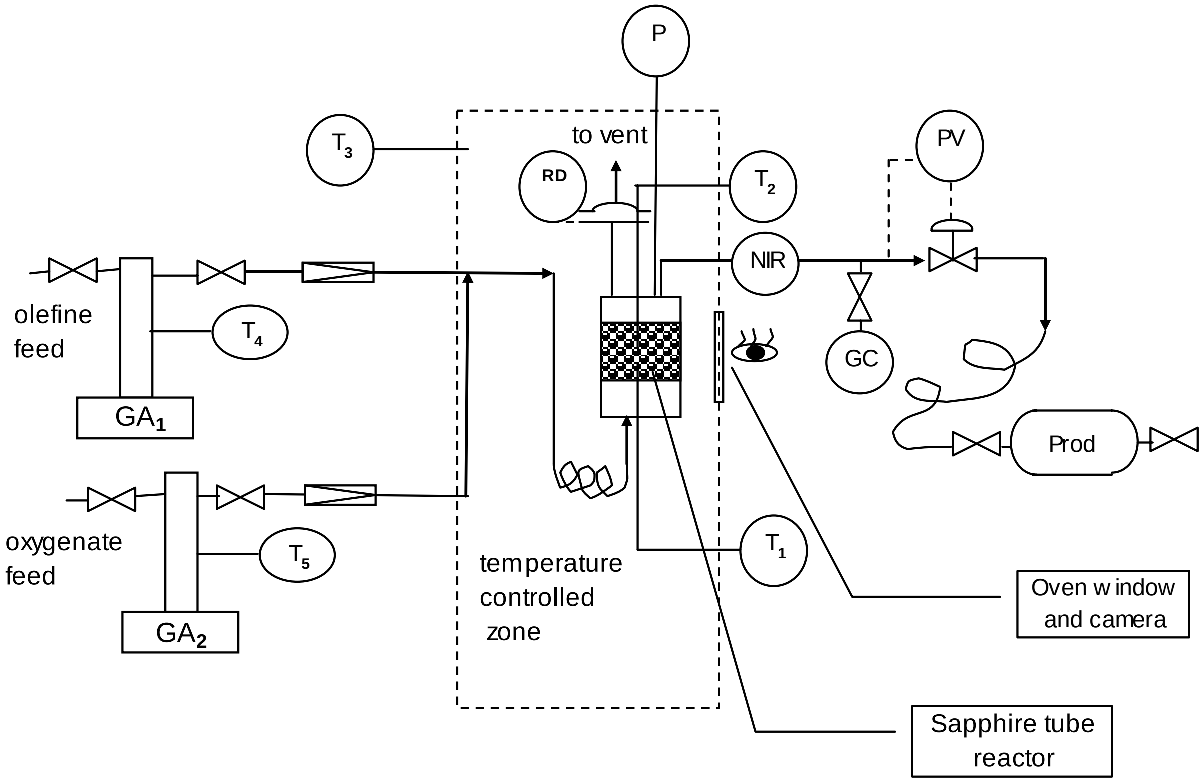

Figure 1. A scheme of the experimental equipment: GA1, GA2 – feed pumps; T4, T5 – pump temperature measurement; T3 – oven temperature regulator; RD – rupture disk (50 bar); P – pressure measurement; T1 & T2 – reactor temperature, NIR – near infra red spectrometer cell; GC – On-line gas chromatograph; PV – pressure control valve; Prod – product container.

DYNAMIC MODEL OF A BUBBLING FLUIDIZED BED BOILER

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A dynamic model for a bubbling fluidized bed boiler is presented. The model is developed to describe dynamic load changes and disturbances in a boiler. The model helps to understand boiler processes like combustion and heat transfer, and also how these processes are connected with each other.

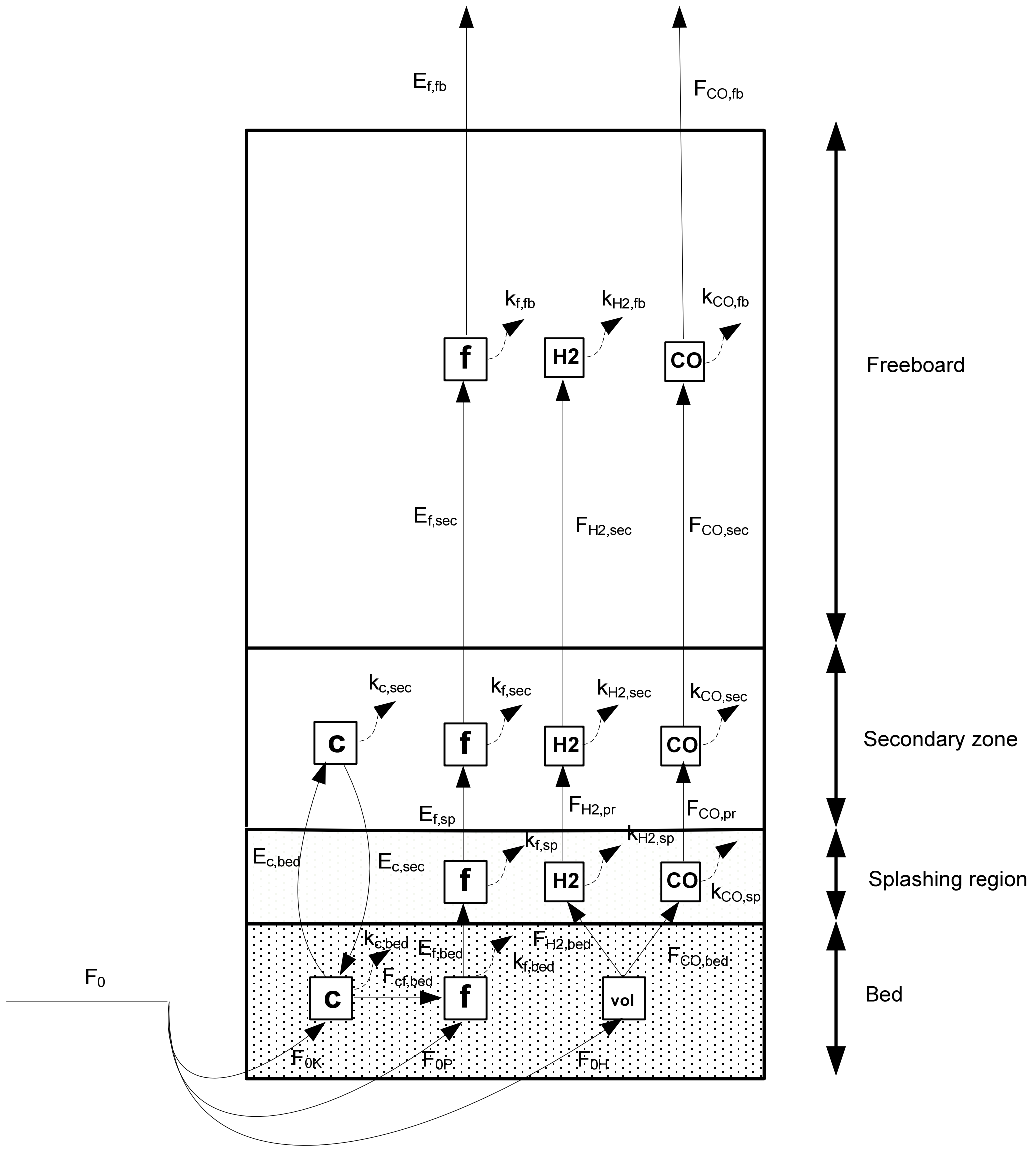
The model consists of air/flue gas cycle (air preheaters, bubbling fluidized bed combustor, and heat exchange section) and water/steam cycle (water preheaters, drum, evaporator, superheaters, and steam cooling). In addition main control loops were included in the model. The simulator is built with MathWorks Inc's MATLAB/Simulink software. The model is a so called first principal model based on physical phenomena. So the model can be modified easily to different size boilers.

Emphasis in the modeling work is put on the furnace model consisting of the dynamic model of the bubbling fluidized bed and heat transfer from the furnace to the evaporator circuit. The fluidized bed model is based on mass and energy balance equations applied to two phase fluidized bed behavior (bubble phase and emulsion phase) and char coal combustion. Attrition and fragmentation of coarse particles are included to the model. The furnace is divided into four segments according to the different type of combustion zones. The structure of the furnace model is shown in fig. 1.

The model is parameterized using a construction data and measured process data from a 260 MW_{th} bubbling bed boiler. The validation of the model showed that the model can describe the dynamics and static gains of the process very well. The model is tested using measured process data as an input to the model and compared computed signals with measured ones.

The model is used to study the dynamic behavior of the boiler process. The points of interest are e.g. thermal inertia and steam storage capacity of the boiler. Knowledge about the behavior of these properties gives useful information for the process and control design. Dynamic model helps process developers to answer questions like how long a boiler can generate steam in case of a boiler trip or what will happen in the process during a black out situation?

The future plans are to test the model by modeling three different size bubbling bed boilers and compare the simulated results with measured ones. Also the user interface of the simulator will be developed to make the build up of the simulator faster. There is also another project going on to develop a similar simulation model for a circulating bed fluidized boilers.



<u>Fig. 1.</u> Structure of the furnace model. **F_0** = fuel feed, **C** = char coal balance calculations, **f** = fine particles balance equations, **vol** = volatile matter balance equations, H2 = hydrogen balance equations, **CO** = carbon monoxide balance equations, **E** = entrainment of char coal from one zone to another zone, **F** = mass flow between model zones.

Session IV.2: Monitoring and Process Data Analysis

Extended abstract submitted to The 14th Nordic Process Control Workshop,
23.-25. August 2007, Espoo, Finland

Untapped Potential in Industrial Process Control

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The process history database is a vital part of a modern process automation system. Originally its main purpose was to be a base for reporting. Even today, the role of such solutions as production reporting, emission monitoring and environmental reporting are in the key role for users in process industries. In addition to this, both operation and maintenance personnel increasingly utilize historian databases for analysis to continuously improve production and maintenance efficiency.

From technology viewpoint, historian databases have progressed according to the laws of computing power: more capacity, more speed and more features for the same prize. Today, a typical historian database may consist of 50000 tags stored for a history of 5 years with a sampling interval less than one minute.

At user interface level, the most advanced process automation systems seamlessly integrate information from both historian databases and real-time Distributed Control Systems (DCS). Real-time process controls, however, typically utilize little or none of long-term data collected into databases. By far the most common tool for analyzing process history is trend plotting. As a result, it is justified to claim that the enormous potential of the data stored in historian databases is not yet maximally utilized. Potential benefits are large both for plant and corporate levels.

The purpose of this paper is to inspire scientists and students to acknowledge the state-of-art technologies used in process industry and existence of this mainly untapped potential. Furthermore, we wish to promote innovative thinking for value-adding ways to utilize the enormous amount of data that is stored in historian databases. We believe that both industrial production and maintenance efficiency may be further increased by developing innovative applications in the area of control, monitoring, and optimization.

In order to illustrate the untapped potential of history data, this paper presents novel industrial solutions for process and equipment diagnostics. These solutions utilize history data and latest possibilities to combine and present such data with other process information. The intent of this paper, however, is more to provoke discussion and further development than to provide ready answers.

Automatic estimation of backlash in valves

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This presentation describes an on-line procedure for detection and estimation of backlash in control valves. The method is automatic in the sense that no information has to be provided from the user. The only information needed, except for the process output signal and the setpoint, are the controller parameters. The effectiveness of the method has been demonstrated through simulations and industrial field tests.

Background

Control valves are subject to wear. After some time in operation, this wear results in friction and backlash that deteriorates the control performance. Therefore, valves have been identified as the major source of problems at the loop level in process control. There are two aspects of the problem. First of all, the nonlinearities deteriorate the control performance. Furthermore, the loops facing these problems often remain undiscovered by the personnel in process control plants. Therefore, it is of interest to have procedures that supervise the control loops and detect stiction and backlash, and procedures for stiction and backlash compensation.

Procedures for stiction detection and for stiction compensation have been available for over a decade, and they are used in many industrial plants today. Compensation for backlash is simple, but these procedures are seldom used in process control plants. The major reason for this is that no efficient backlash detection and backlash on-line estimation procedure have been presented.

The estimation procedure

Figure 1 shows a part of a simulation of a control loop with backlash in the valve. The signals show the typical pattern obtained when a process is controlled by a PI controller and when there is backlash in the control loop. The process output remains a distance Δy from the setpoint while the control signal drifts through the dead band caused by the backlash. When the control signal has changed an amount Δu, the process output is moved towards the setpoint. The time instances when the process output crosses the setpoint are marked in the figure. The time between these zero crossings is $\Delta t = t_{i+1} - t_i$.

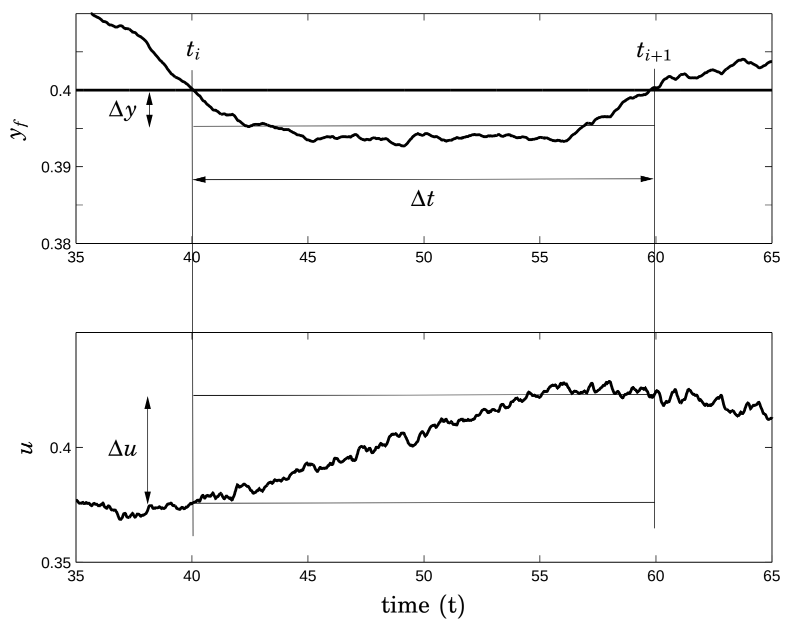

Figure 1 Part of a simulation of a control loop with backlash. The upper graph shows the process output and the lower graph shows the control signal.

The backlash estimate is given by

$$\hat{d} = \left(\frac{K}{T_i} \Delta t - \frac{1}{K_p} \right) \Delta y. \tag{1}$$

where $\hat{d}$ is the backlash estimate, K is the controller gain, T_i is the integral time of the controller, and K_p is the static process gain.

The information required to determine the backlash on-line is the controller parameters K and T_i, and the static process gain K_p. If the process gain K_p is unknown, a default value $K_p = 1.5$ can be used. Further, it is necessary to measure Δy , e.g. by integrating the control error between zero crossings, and the time Δt between zero crossings. Note that it is not necessary to have access to the control signal u.

Results

The backlash estimation procedure has been tested through simulation experiments as well as industrial tests in a paper mill. The results indicate that this is a robust and efficient way to detect backlash and estimate the amount of backlash in control valves.

Reference

The estimation procedure is presented in

Hägglund, T. (2007): "Automatic on-line estimation of backlash in control loops." *Journal of Process Control*, **17**, pp. 489–499.

OFFLINE TESTING OF THE FTC-STRATEGY FOR DEAROMASATION PROCESS OF THE NAANTALI REFINERY

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Abstract: In this paper, a scheme for using process monitoring information in process control is presented. The behaviour of an industrial dearomatisation process operated under model predictive control (MPC) is studied in the presence of faults in an online product quality analyser. Different fault tolerant control (FTC) strategies relying on fault detection information provided by process history based quantitative methods are studied utilising both a dynamic process simulator and the MPC. It is shown, that the inherent accommodation properties and model information in the studied MPC provide means to realise the proposed types of FTC strategies.

Keywords: Fault tolerant control, Dearomatisation process, Model predictive control, Process monitoring, Data-based modelling, Online quality analysers

A SOM-based Approach for Analysing and Modelling a Wave Soldering Process

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I. Introduction

Today, new environmental regulations are forcing the electronic industry to reduce and even cease the usage of hazardous products, such as lead-bearing materials and substances containing volatile organic compounds (VOC). Thereupon, the implementation of the lead-free and low VOC processes sets new requirements for process optimization also in the case of wave soldering, because the earlier process conditions confined for lead containing manufacturing materials may not be applicable to the lead-free process as such. Hence, it can be considered as an advantage, if the manufacturing processes in the electronic industry can be optimized by data-driven modelling. In such situation, the experimental activities and testing can be diminished. Additionally, a good computational model helps in reducing the costs of learning through trial and error, which makes the manufacturing process more efficient.

The benefits of the neural network modelling method are in its flexible modelling abilities and in its ability to reveal nonlinear and complex dependencies. Moreover, some recent studies have already indicated that artificial neural networks can be considered as a useful and efficient method for modelling the industrial type of data [1-6]. However, the applications have this far been principally in the field of dynamical processes, such as energy producing, while examining application possibilities in the electronics industry has been quite restricted. Thus, the examination of the more discrete manufacturing processes, such as wave soldering, requires some further attention.

II. The wave soldering process and the data

The acquired process data consisted of process information gathered from some test measurements, in which PCBs were put through the wave soldering process using a lead-free solder. In the case of the modelling data, only water or low VOC -based fluxes were used in the fluxing phase of the soldering process. The size of the used data matrix was 418x40 (418 rows, 40 variables in columns), and the data variables included mostly various process parameters, but also some solder defects as a measure of the solder quality.

III. Modelling methods

The data was coded into 11 inputs for the self-organising map. All input values were variance scaled. The SOM having 225 neurons in a 15x15 hexagonal arrangement was constructed. The linear initialization and batch training algorithms were used in the training of the map. A Gaussian function was used as the neighbourhood function. The map was taught with 10 epochs and the initial neighbourhood had the value of 6. The SOM Toolbox [7] was used in the analysis under a Matlab-software platform (Mathworks, Natick, MA, USA).

The K-means algorithm was applied to the clustering of the trained map. The K-means method is a well-known non-hierarchical cluster algorithm [8]. The basic version of the K-means is started by randomly selecting K cluster centres, assigning each data point to the cluster whose mean value is closest in the Euclidean-distances-sense. Then, the mean vectors of the points assigned to each cluster are computed and used as new centres in an iterative approach.

IV. Results and discussion

The map was obtained by training a self-organizing network using the soldering data as inputs. The map is shown in Fig. 1 a). The SOM map was then clustered according to the ten known flux types by using the K-means algorithm. These clusters are also illustrated in Fig. 1 a).

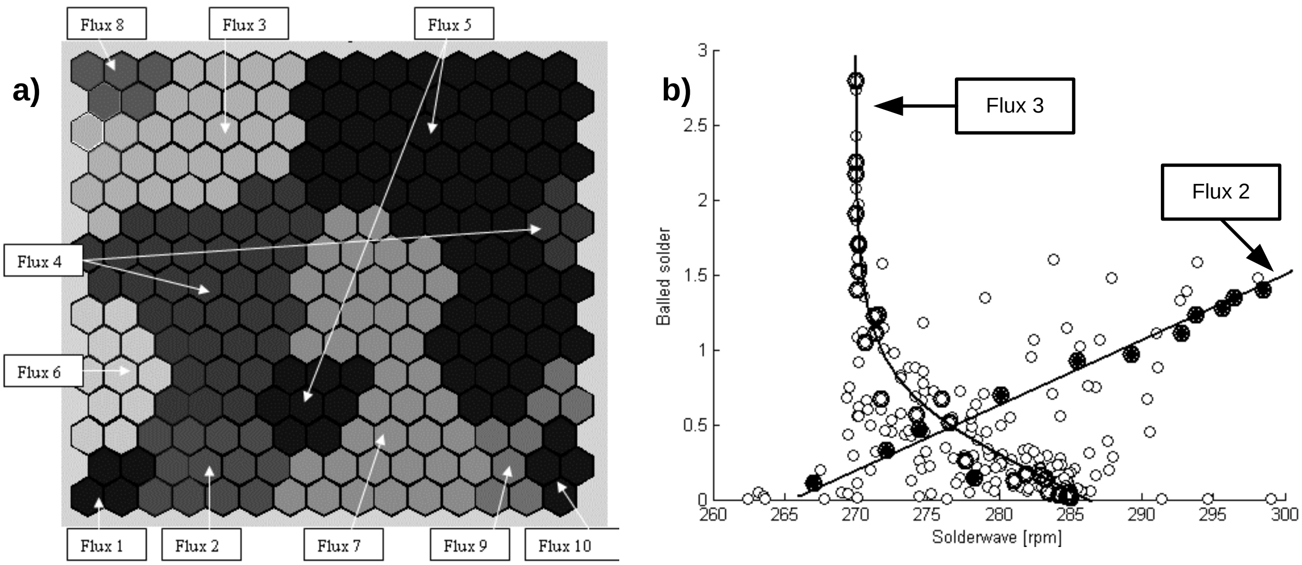

Fig 1. a) SOM using the data of a soldering process. The background colours visualize the ten clusters of the map. b) The number of balled solders is presented as a function of the solder wave [rpm].

As a result of the flux-specific inspection, some interesting multidimensional dependencies between process variables were found after the clustering of the modelled wave soldering process. For example the number of balled solders is presented as a function of the solder wave in Fig. 1 b). A tremendous variation between the behaviour of different flux types can be clearly observed. In the case of flux 2, the appearance of balled solders decreases with the growth of the solder wave intensity. Contrary to this, in the case of flux 3 the number of balled solders on the PCB increases linearly with the solder wave. These results presented here clearly indicate that this kind of approach is a useful way in the modelling of the wave soldering process.

The implementation of the lead-free processes sets new requirements also for the optimization of the wave soldering process optimization, because the earlier process conditions confined for lead containing manufacturing materials may not be applicable or at least optimal anymore. In this respect, the successful computerized modelling of the process has several advantages including the reduction of the process costs; a more efficient process and a reduced material loss are achieved as learning through trial and error is diminished. Hence, the correct adjustment of the wave solder process is important to produce soldered PCBs with high quality and to minimize ineffective process tuning.

V. Conclusion

The results presented in this paper show that the applied SOM-based neural network method can be an efficient and fruitful way to model the type of data acquired from the electronics industry. By means of the obtained data-driven model, some unparalleled findings were discovered with respect to the dependencies between the process parameters and some solder defects.

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Data Driven Controller Tuning

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Keywords : Controller tuning, Iterative Feedback Tuning, Invertory control

Optimal performance of process control requires a controller synthesis based on a performance criterion. In order to minimize the criterion, a model for the process is normally required. Iterative Feedback Tuning (IFT) is a data driven methodology to tune controller parameters given a performance criterion, with penalty on the controlled variable deviations from a desired trajectory and with penalty on the control variable it self or it's increment. The methodology was published first time in [1] and have since been extended and tested for a number of applications [2]. The method minimizes the performance criterion using a gradient based search method. The gradient is estimated through three closed loop experiments, designed to give a consistent estimate. The first experiment provides input/output information of the system and the two remaining experiments are used to form an estimate of the gradients of the input and output with respect to the controller parameters. Using closed loop data is an advantage, not only with respect to the operation of the process, but it is also desired from a control design point of view, since it is the loop performance that is subject to optimization.

The advantage of IFT relies on the ability to achieve the desired performance in few iterations. Plant experiments are costly and product produced under an experiment may have reduced quality since the process is perturbed from it's normal point of operation. Tuning controlleres for the disturbance rejection problem, IFT may only converge very slowly. A method to insure high information content in data and hence a fast convergence is illustrated for this type of problem.

IFT is sugested for tuning of inventory controllers. Since the method relys only on closed loop data it is able sytematicaly to handel the modeling bias which affect the feedforward proberties of the controller [3]. Even though inventory controllers can be nonlinear, the derivatives of the controller with respect to the parameters in the optimization are stable linear filters as required. Level control on a mutivariable pilot plant is used to illustrate performance of IFT for inventory control.

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AN EMBEDDED FAULT DETECTION, ISOLATION AND ACCOMMODATION SYSTEM IN A MODEL PREDICTIVE CONTROLLER FOR AN INDUSTRIAL BENCHMARK PROCESS

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Abstract: The fault detection and isolation (FDI) in industrial processes has been under an active study during the last decade, but fault tolerant control applications that rely on traditional FDI methods have not been widely implemented in industrial environment so far. The most widely implemented FDI methods have traditionally based on model-based approaches. In the modern process industries, however, there is a demand for methods based on the process history data due to the complexity and limited availability of the mechanistic models. In this paper a fault tolerant model predictive controller (MPC) with an embedded FDI system is presented for controlling a simulated crude oil fractionator process, Shell Control Problem (SCP). Three FDI algorithms are applied for achieving the fault tolerance in co-operation with MPC: system based on Principal Component Analysis (PCA), Partial Least Squares (PLS) and Subspace Model Identification (SMI). In addition of the FDI part, fault accommodation part with measurement reconstruction and reference trajectory tracking is implemented. The effectiveness of systems is tested with bias and drift faults in the simulated process measurements. Finally, the results are presented and discussed.

Keywords: FTC, FDI, PCA, PLS, SMI, MPC, shell control problem.

Session V.1: Papermaking and Mineral Processing

ENHANCED CAUSAL DIGRAPH REASONING FOR FAULT DIAGNOSIS WITH APPLICATION ON THE PAPER MACHINE SHORT CIRCULATION PROCESS

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Extended Abstract:

The aim of our research is to develop the fault diagnosis method on the process component level and apply it in the paper making process. A great demand from different industries has driven the development of fault diagnosis research. Due to the increasing competition in the process industries, there has been a strong need to detect, locate and estimate the faults and recover the process from faulty states. By providing the supportive information to the operators or recovering the system automatically, the fault diagnosis keeps the process running efficiently and safely, which brings enormous economical benefits to the industries.

Fault diagnosis is considered as the identification of the type, size, location and time of the fault after the detection, which will provide the necessary information for the process recovery or protection. The knowledge of the process, measurements and the results from fault detection are usually used to perform the fault diagnosis. During the last decades, numerous methods for fault diagnosis were developed. According to the way how these methods utilize information, they are categorized into two groups: the process data based methods and the knowledge based methods.

As the drawback, the applications of these methods are seldom found in the industries. One of the most important reasons for this is that most of the methods consider only the process variables rather than the process component. The results obtained from these methods tell little information about the status of process component which is actually interested for industrial people.

The methods used for our fault diagnosis on the level of process component are causal digraph method and parameter estimation method. The causal digraph presents an excellent way to integrate the process knowledge with the process data. Moreover, the inference rules provided by causal digraph can handle various types of faults: sensor, actuator and process dynamic. On another hand, the latest development of parameter estimation method (state and parameter dual estimation) makes it possible to handle nonlinear time-variant process with consideration of the process and measurement noise.

The proposed strategy for fault diagnosis on process component is to combine these two methods described above and utilize the benefits of both. The causal digraph method was used first to isolate the fault inside subprocess and narrow down the number of parameters need to update. The parameter estimation method was used then to identify the parameters for the cause-effect model in the causal digraph. The last step is to establish the mapping between the model parameters and the physical parameters. The updated model parameters will be interpreted with this mapping and the information about the condition of the component can be obtained and used for the process recovery and maintenance scheduling.

The proposed method was tested with MATLAB/SIMULINK and the advanced paper machine simulator (APROS, VTT), which give promising result and the application in industry is expected.

Keyword: causal digraph, parameter estimation method, APROS

Estimation of 2-dimensional variation on the basis of irregularly moving scanning sensor

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Typically, the quality of a paper web is measured by a regularly moving sensor which takes measurements along a zig-zag path over the web. On the basis of these measurements 2-D variation and separate temporal and spatial components need to be estimated for control. Moving the sensor irregularly provides a possibility to get additional information about the variations, for example occasional estimation of spatial actuator responses during normal operation. Furthermore, as the web is controlled based on the estimates of spatial and temporal variations, scanner movement is an unused degree of freedom in control [1].

Current scanner systems estimate the spatial estimate for control either by averaging the last 6-10 scans or with a corresponding exponentially weighted moving average (EWMA) filter over scans. Temporal estimate is the average of the spatial estimate at each time instant. Such estimation method is not suited for irregular scanning. For example, when the sensor is stopped for a while or when the movement direction of the sensor is changed in the middle of the web, the control must be put on manual.

We present a simulator for 2-D quality variations of the paper web. The variation is a combination of user defined component and simulated actions of spatial and temporal controls, however, implemented as rather simplified and idealized. User may define an arbitrary movement of the sensor.

The estimation method in the simulator updates spatial and temporal estimates at every time instant. Measurements are described as Gaussian non-biased probability densities. The system model for estimation is a set of independent random walks at each spatial location, with a diffusion constant *D*.

The web estimate of a quality variable $\hat{x}(i, j)$ is computed from sensor measurement and position signals. In spatial positions that are not measured, the updated estimate is the previous estimate and the variance is increased (Equations on left) with $D\Delta t$. In positions that are measured the new estimate is a Bayesian combination of previous estimate information and new measurement information and is given as (Equations on right):

$$\hat{x}(i, j) = \hat{x}(i-1, j) \qquad \hat{x}(i, j) = \frac{\left(\hat{\sigma}^2(i-1, j) + D\Delta t\right)x_{meas}(i, j) + \sigma^2_{meas}\hat{x}(i-1, j)}{\sigma^2_{meas} + \hat{\sigma}^2(i-1, j) + D\Delta t}$$

$$\hat{\sigma}^2(i, j) = \hat{\sigma}^2(i-1, j) + D\Delta t \qquad \hat{\sigma}^2(i, j) = \left(\frac{1}{\hat{\sigma}^2(i-1, j) + D\Delta t} + \frac{1}{\sigma^2_{meas}}\right)^{-1} \tag{1}$$

where $\hat{x}(i, j)$ is the value of web estimate, $\hat{\sigma}^2(i, j)$ is the variance of the quality estimate, $x_{meas}(i, j)$ is the value of the measurement, σ_{meas} is the measurement uncertainty and $D\Delta t$ is the random walk diffusion. The temporal estimate is the mean value of $\hat{x}(i, j)$ over spatial index j, and spatial estimate is $\hat{x}(i, j)$ with temporal estimate subtracted. This estimate can be interpreted EWMA with nonuniform sampling. Hence, in spite of its simplicity it is a natural extension of current practice both for regular and irregular scanning.

Figure shows an example of web variation and its estimate when the web is scanned irregularly.

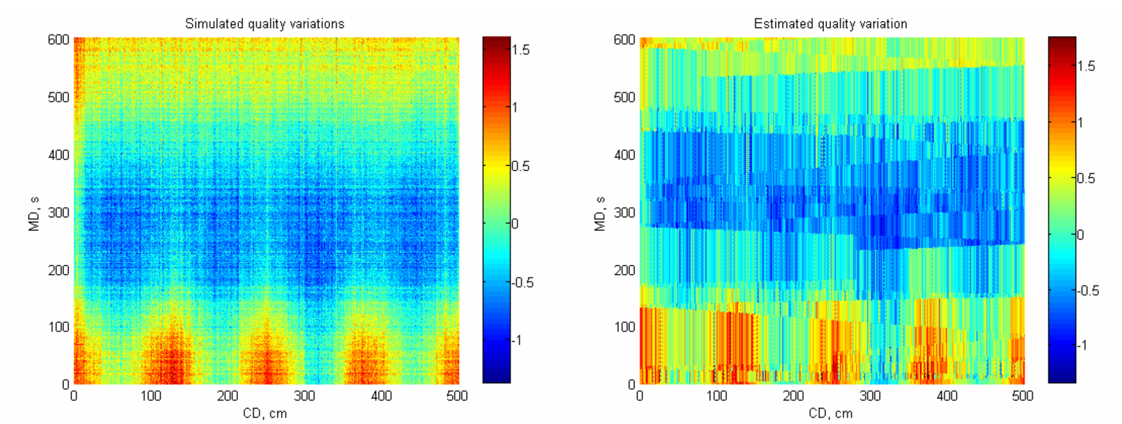

Figure. (a) Simulated quality variations of the paper web. (b) Estimated quality variation with the simple method with sensor traveling along an irregular path. Sensor path is visible as change points of the estimates.

The estimation method is also a Kalman filter with process model:

$$
\begin{aligned}
&x(k+1) = x(k) + \sum_{i=0}^{d-1} G(k,i)u(k-i) + v(k) \\
&E\{v(k)v(k')\} = \delta_{kk'} R(k)
\end{aligned}
\qquad (2)
$$

with controller actions neglected and $R(k) = Id \cdot D\Delta t$. With the process model (2), the estimation method can be easily extended with the effect of controllers and noise model as a tuning parameter. Indeed, such methods have been reported in literature, but current systems do not apply them [2,3]. Note that the random walk structure of (2) differs from the models for control. Here the model is intended only for observation and thus worst-case dynamics has been chosen. Choosing G(k,i) as time difference of impulse response function, regular response functions are obtained.

The simulator provides a tool for researching the effects of scanner movement on the estimation and control of the paper web. Optimizing the scanner path as part of the control is a complex optimization problem. With the process model (2) the optimal path is the regular scanning path. Therefore irregular scanning will be triggered by spatially non-uniform or time-varying noise term, or by need to estimate response models during normal operation. Conditions and opportunities of irregular scanning will be discussed.

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Improving Profile Estimation on Paper and Board Machines

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KEY WORDS quality control system, profile estimation, Bayesian, Kalman, ARMA

ABSTRACT

Traversing scanners are still widely used in the online measurement of product quality variables on paper and board machines. The whole web width sensing devices are available only for some variables, like moisture. A papermaking process is very complex and the quality information from a traversing scanner is very sparse compared to process complexity. A traversing scanner measures from a zig-zag path and it procedures measurement data with its different variations. The feedback control is only possible separately in machine direction (MD) and cross direction (CD) and thus the scanner measurement data has to be separated into MD and CD components.

There is increasing interest in the use of advanced methods in the CD and MD profile estimation due to the high quality requirements of paper and board products. Implementing new estimation methods into online quality control systems needs a testing environment. A Matlab based quality control simulator is developed for the assessment of new and existing profile estimation methods and control algorithms. New profile estimation methods, such as Bayesian, Kalman filter based and ARMA model related, are presented. The influence of these new estimation methods on the CD and MD control performance is focused and simulation results are available.

As a result we get new information on the functionality and performance of CD and MD profile estimation methods. With a better profile estimation the functionality of CD and MD control loops may be improved: the variations become smaller and the controllable quality variables come more quickly to their steady states after grade change and disturbance situations. The quality measurement data estimation is studied in the TEKES MASI NoTeS research project under the guidance of professor Risto Ritala at the universities of TUT, LUT and KyAMK in 2006 – 2007.

SOFTWARE FOR FILTRATION DATA ANALYSIS (FDA)

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A traditional pressure filtration cycle is divided into different stages: filtration, pre-wash compression, pre-wash displacement, washing, compression and displacement. Only the filtration and compression stages are necessary, but the use and the order of the other stages depends on the quality requirement of the product. During a filtration cycle, hundreds or thousands of rows of data are gathered. The analysis of this data is laborious and there is a risk of miscalculations. Therefore, software was developed for easy processing and modelling of the data from the filtration tests. In the software different process stages were considered as the discrete entities and analysed individually (Salmela & Oja 2005).

When the input values and the data from the filtration run are given for the software, it draws a figure in which the mass of filtrate is shown as a function of time on the right y-axis, and the filtration and compression pressures as a function of time on the left y-axis. The user of the software is able to choose the process stages, which are included in the test. Then the user determines the start and the end point of each included process stage from the figure by moving the vertical lines showing these points on the figure. Then the software draws the experimental results and the corresponding results calculated from the models associated to each stage, and gives the average pressure during each stage, as well as the certain result parameters of each stage, as output.

The different process stages of the filtration cycle are commonly treated individually. No-one has gathered them together for data analysis purposes. Although in this study the filtration cycle analysis is developed for the starch filtrations, it is possible to use this software for the filtrations of all the materials, which have a similar type of behaviour to one of the starches during the filtration cycle. It can be commonly used as the analysis tool for the systematic filtration data analysis. In the future, it could also be possible to extend the software to correlate the data for different process stages for designing a filtration cycle, and to indicate what happens, if some parameter is changed. Possibly, the software could be used for the optimisation of the separation processes in the future too.

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EXPERIENCES IN CHARGE VOLUME MEASUREMENT AND THE POTENTIAL OF MODELING

By Jussi Järvinen, Heikki Laurila, Jarkko Karesvuori and Peter Blanz

INTRODUCTION

Autogenous and semiautogenous grinding have high running costs and use energy inefficiently, which makes them interesting unit operations when it comes to performance optimization. Changes in ore properties affect the impact breakage efficiency and therefore the efficiency of the whole grinding process. As a result, the efficiency and optimal operating parameters constantly change. Although the effectiveness of grinding is affected by many factors that are difficult to measure, most are linked to the charge behavior and its properties. Although the charge volume in itself is valuable for process control purposes, this novel information also opens up new possibilities when used in models. Such an example is ball charge estimation, which is feasible only when indications of the charge volume and mass are used.

CHARGE VOLUME FROM SPECTRAL PROPERTIES OF POWER

Outotec has developed a non-contact method for determining the charge volume in a grinding mill based on a ripple in the power draw of the driving motor. The ripple is caused by the mill's lifters that impact the toe of the charge and cause a peak in the power drawn by the mill. When the toe of the charge moves (e.g. due to a change in charge volume or mill rotation speed), the ripple will also move such that a single peak comes either earlier or later. (Järvinen, 2004) The original idea was conceived during 1989 – 1990 at the Pyhäsalmi concentrator (presently owned by Inmet Mining Corporation) in Finland (Koivistoinen et al., 1992). Recently, Outotec has developed the concept further to produce a robust analyzer called MillSense. It uses a high-frequency sampling of the mill current draw and a proximity switch to synchronize the measurements to the mill rotation. No other measurements or sensors are required and therefore the installation and testing is simple and maintenance requirements are low. The analyzer interface is available remotely via a built-in Web server through an Ethernet connection. This connection has been used, for example, to monitor the analyzer installed at Pyhäsalmi concentrator to provide support and software upgrades

THE EXTENDED KALMAN FILTER IN BALL CHARGE ESTIMATION

One of the key factors in the optimal operation of a semiautogenous grinding mill is the rock-to-ball ratio. In most cases, however, it is impossible to determine the ball charge without stopping the mill. It would be intuitively appealing to use a model of some kind to compute the ball charge from the power draw and other related variables. However, there are several sources of fluctuation – such as ore packing and slurry pooling – in the mill power draw that none of the current power models properly account for. Additionally, there are several quantities, such as ore density, that might be modeled, but cannot be measured on-line in the majority of cases. Therefore, an extended Kalman filter (EKF) with fully user-definable equations has been implemented in MillSense. The Kalman filter has been extensively covered in existing literature (for example Maybeck, 1979). Therefore, the equations will not be repeated in this article. The easily configurable structure of the EKF in MillSense makes it possible to utilize even relatively complex models for estimation purposes. For example, Morrell's mill power model (Morrell, 1996) has been successfully used as a means for ball charge estimation. Naturally, the EKF needn't be limited to ball charge estimation alone.

LINER WEAR AND CHARGE MOTION

The mill lining has a great impact on the overall grinding efficiency and the difference between a new liner and a worn-out liner can be dramatic. In addition to being able to predict the necessity of a reline, on-line knowledge of the extent of liner wear provides crucial information about the grinding efficiency. A geometrical model of the liner is currently being developed as a part of MillSense in order to estimate the liner wear as a function of throughput and possibly the abrasive effect of balls impacting the liner. The model can be calibrated easily with basic lifter dimensions measured from worn lifters. Calibration to lifter profiles presented in literature has been successful in providing realistic wear estimates. Work is under progress to do industrial-scale lifter profile measurements in order to study and validate the wear estimates more closely.

Having a realistic estimate of the state of the liner available makes it possible to provide good estimates of the grinding media trajectories. Based on the liner wear estimation and measured mill speed, a physical model describing the motion of a single ball can be constructed. This approach has been reported in literature (Powell, 1991), but further enhancements to this model are required in order to produce realistic trajectories and information (e.g. charge and liner impact energies), which can be used in grinding control. A physical model for the ball trajectory has been implemented with several enhancements and comparisons to results reported in literature from DEM and pilot mills have shown good accuracy.

CONCLUSIONS

Recent development of MillSense aims at providing further information on the state of the mill in addition to the toe angle and charge volume. An accurate charge volume measurement combined to ball charge, liner state and charge motion estimates should prove very useful from a control application's point of view.

ACKNOWLEDGEMENTS

The authors would like to thank Inmet Mining Corporation for allowing the tests to be carried out at Pyhäsalmi concentrator and their support in the on-going project.

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Session V.2: Control Applications

Optimal Operation of a 4-product Integrated Kaibel Column

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April 13, 2007

Abstract

This paper considers the Kaibel column, a fully thermally coupled distillation column for the separation of four products in a single column with a single reboiler. The main reason for considering the Kaibel column is probably the potential capital savings compared to conventional arrangements with 3 columns in series. The authors of this paper have built a laboratory pilot plant of a Kaibel column with the purpose of investigating its operational performance and its control properties. The term "optimal operation" is rather ambiguous unless the operational objective is also clearly defined. In this article we present 4 different cases where the objective for optimal operation varies. The cases include minimizing the energy consumption given product specifications, minimizing product impurities with fixed energy input and two cases where we maximize profit given product and energy costs. For all cases, the minimum singular value-method is used to select the best locations of temperature measurements for stabilizing control of the column profile. The resulting control structures are then compared, with attention to the disturbance loss with respect to the different objective functions. We also provide experimental results from the implementation of one of the control structures on the laboratory pilot plant.

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COMPENSATING THE TRANSMISSION DELAY IN NETWORKED CONTROL SYSTEMS

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Extended Abstract

Automation systems of the future and even those currently in use today, will consist of a large number of intelligent devices and control systems connected by local or global communication networks. In these Networked Control Systems (NCSs), communications between process, controllers, sensors and actuators are performed through the network.

In most cases, the insertion of the network does not significantly affect the performance of the control system. However, for some time constrained systems (constraints coming from the dynamic of the physical process to observe and to control), the implementation of the NCS should be done considering the implications introduced by the network. For such systems, the insertion of the communication network into the feedback control loop introduces an additional delay, either constant or time varying, that makes the analysis and the control design more complex.

Studying the networked control systems requires the evaluation of the Quality of Service level provided by the network and integration the values of these QoS parameters in the control design. One of the main limitations of the previous research on NCS is the lack of integrated control design and network evaluation. It is often assumed that either the control is specified (information timing constraints exists) or the performance of the network is well-defined (information about the delay distribution, uncertainty, deviation from mean value, missing value rate is assumed known). The results for the whole design cycle, where the network evaluation and control are integrated and performed the same context, are still lacking.

In this paper the whole design cycle for the NCS will be presented. Two novel integrated approaches will be presented that differ in the exactness of information available from the network. In the first one the measured information about the network performance will be directly integrated in the control algorithm. In the second approach the estimated information about the network performance will be utilized in the control synthesis.

The first integrated approach is applicable in the case where it is possible to implement the measurement algorithm in each device and to integrate in the frame format (for example on application level) special tags (time stamp, frame number, etc). The second procedure, on the other hand, requires a priory knowledge of the traffic and the network architecture.

The objective is not to obtain the optimal control strategy over the communication network nor the precise estimates of the network properties but to emphasize the benefits achievable when the network and control are considered simultaneously.

Keywords: Networked control systems, delay compensation, real time systems

This research has been conducted as a part of the Networked Control Systems Tolerant to Faults (NeCST) project IST-004303 that is partially funded by the EU. The authors gratefully acknowledge the support.

REQUIREMENTS FOR MODERN ADVANCED CONTROL TECHNOLOGIES IN THE HYDROCARBON INDUSTRY

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KEY WORDS: advanced process control, dynamic real time optimisation, fault tolerant control, model predictive control, hydrocarbon industry

EXTENDED ABSTRACT

In this paper, the requirements that the oil and petrochemical industry sets for advanced process control (APC) applications are discussed. The modern processes in the hydrocarbon industry are large, complex and produce a wide variety of products from a spectrum of feedstocks. Some advanced control approaches that are used by the industry to tackle the characteristics of the processes as well as some lessons learned are presented.

In the modern hydrocarbon business, the agility of the plant adaptation to opportunities may become decisive for its success. This is mainly attributable to dynamics in throughput and capability to handle process constraints. There are often several feedstocks processed as such or as blends with other streams. Furthermore, several products are generally produced simultaneously. Because storage capacity is limited and feedstock availability or product sales opportunities require swift action, feedstock and product slate changes are frequent in addition to other plant operations. All these operations cause the plant to be in transient states a large fraction of its on-stream time. Furthermore, many feedstocks often vary either dynamically or from batch to batch and may be further dynamically mixed in storage tanks and feed systems. In the industrial processes, there are recycle streams that are necessary to drive the processes to acceptable conversions and recoveries. This dynamically affects the composition of process streams and subsequent processing characteristics. It is mandatory for any advanced control scheme to be able to catch the nature of the processes and to be capable of handling frequent transients.

Not only the process technology but also the existing automation places demands on the advanced control applications. The field instrumentation of industrial processes might be incomplete, and the advanced control technologies have to manage possible sensor faults. In the hydrocarbon industry, the compositions of certain important process streams are measured with online process analysers. Hence, the online analysers play a key role. It is thus required that the advanced control applications can handle the long, and generally varying, time delays caused by analysers. The APC applications should also be provided by means for detecting and isolating possible faulty analyser results. The process automation systems (DCS) also set some constraints to the advanced control applications. The advanced control application must be protected against failures in the communication between the APC application and the DCS.

Model predictive control (MPC) is widely exploited for advanced control applications in the hydrocarbon industry. However, the traditional textbook paradigm of MPC where the emphasis lays on the controlled variables that are driven to their respective target values has proven somewhat inadequate. Instead, the constraint handling capabilities of the MPC algorithm are of great importance for the industry. In addition to that, the algorithms used are often complemented with features that detect analyser faults by simple logic functions. As the demands grow, fault tolerant control (FTC) will be a significant factor in future APC applications. On the other hand, there has been an increasing interest in applications that dynamically optimise the production of the plant taking into account the constraints of the plant. There are some excellent dynamic real time optimisation (DRTO) applications that have resulted up to 10 per cent increase in the production of the process plant [1, 2].

Dynamic Real Time Optimisation

There is an increasing need for full scope solutions that optimise the production of the process plant taking into account the plant objectives, constraints, dynamics, structure and available resources. These applications are working in conjunction with the model predictive controllers. The applications are based on evaluating the plant economy dynamically each minute or essentially in real time. The complex network of cause and effect is solved simultaneously by the DRTO to trade off the different final economics. Maximising the process plant profit has led to solutions where production volume profit clearly dominates over the recovery and utility costs at the constrained optimum. Fortunately, this type of solution leads to a very consistent optimum policy: utilities are used as much as required to meet the product specifications and the constraints are ridden as tightly as possible to accommodate maximum production rates.

Although some plants may operate occasionally at less than full capacity and the DRTO then acts to make the most profitable selection of independent variables, it can be anticipated that most of the time plant economics is driving to maximum use of the installed capacity. In consequence, the DRTO will operate most of the time against a number of different simultaneous constraints and control requirements. In this constrained regime the ability of DRTO of riding the frequent transient states, becomes even more important and will swiftly move to the optimal production.

In cases where the optimisation opportunities are dominated by resource allocation, such entities are favoured in which feed is inexpensive, production value is high, or can be made high through DRTO moves. Excessive process loading is efficiently counterbalanced by diverse process constraints, and in some cases overcapacity cost functions. All plant processes become swiftly optimised and constraints approached since the dynamics are considered and optimisation is executed typically each minute.

Fault Tolerant Control

The operation of a modern control system needs to remain satisfactory in situations where a fault has occurred in the controlled plant or in the controller itself. Fault tolerant control allows the plant to remain operable under faulty conditions even though performance sacrifices may need to be accepted. Fault tolerant control does not only cover process safety; it includes increased productivity and profit as well. Fault detection and isolation (FDI) is an important part of fault tolerant control systems if not the most important. It is usually also the most difficult task to carry out. Without FDI, the FTC capabilities of the control systems tend to be very limited. In the industrial environment correct FDI is emphasised. The problem is twofold: false alarms lower the operators' confidence toward the FDI whereas missed alarms suppress the benefits of FTC.

Previous work has demonstrated that model predictive control can readily be exploited as a vehicle to realise different types of FTC strategies. For example, it has been shown that with smart FDI an MPC controller is able to tolerate sensor faults with its inherent prediction and accommodation properties. It seems that in the future MPC software includes built-in portfolios of general FTC strategies for various industrial processes. The feasible FTC strategies are diverse: updating the controlled variable (CV) predictions with faulty measurements can be temporarily stopped, CV set points can be slightly modified to cancel the accumulated effects of incipient faults, the MPC constraints can be changed etc. [3]

Dynamic Process Simulation in Hydrocarbon Industry

Dynamic chemical engineering simulators have demonstrated their usefulness in modelling complex chemical processes that exhibit several interactions. Benefits have been achieved in control system design, safety planning, studying the fundamental phenomena governing processes and particularly in operator training [4]. In the case of a plant under construction, the operators can train in advance shortening the training period after plant construction is complete. In the case of a plant already in use, the operators can e.g. go through simulated fault scenarios, enabling the operators to become familiar with more infrequent disturbances preventing possible major upsets in the future. All this adds up to the availability time of the plant improving economics. Also, dynamic chemical engineering simulators equipped with thermodynamic databases and calculation methods, component libraries as well as template elements for different process equipment have proven their value in the industrial setting when compared to more generic dynamic simulators lacking these features.

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Optimization and Simulation Application for Expandable Polystyrene Batch Process

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1. Introduction

Batch processes are typically based on predefined process recipes. If process circumstances, chemicals and recipes are constant, the product should basically be always the same. A batch process is also commonly used for producing Expandable PolyStyrene (EPS). However, in practice this polymerisation reaction is a very sensitive process and numerous variables affect it, which makes the process difficult to control. The EPS production has to be able to follow fast the aims and quality requirements of the market, which causes additional demands on the process control.

Archived process data is an important resource for the knowledge management of the process and it can be used for the optimization and improvement of productivity. Recent applications have demonstrated that artificial neural networks can provide an efficient and highly automated method for modeling industrial data [1, 2]. In particular, studies, which use standardized protocols, are most likely to benefit from automated artificial neural networks (ANN) analysis [1-5].

In this study we demonstrate optimization and simulation application for EPS-batch process. The application consists of a production optimization tool and also a simulation tool, which is based on Multi-Layer Percetron network (MLP).

2. The EPS-batch process

The studied process was a typical suspension polymerisation batch process, which is commonly used for producing EPS (Expandable PolyStyrene). The polymerisation stage is executed in a pressure-temperature range below the boiling point of styrene-water suspension system. After the polymerisation stage the process continues into the impregnation stage, where the blowing agent is impregnated into the beads. The biggest challenge in the suspension polymerisation process is to achieve the required bead size distribution divided into fractions.

3. The application

The application has process optimization and process parameter simulation tools. The software is made using Matlab software platform (Mathworks, Natick, MA, USA).

3.1 The tool for optimization of the process

The question of optimization is how the production can produce an optimal amount of bead size fractions defined by requirements of the market. Figure 1 illustrates the optimization tool, where the user can define bead size fractions, production of tons, amount of styrene, polymerization temperature and product type. The software calculates optimal combination of distributions qualifying for inputs given by the user. Historical data and statistical methods are used in calculations. In addition, there are plenty of visualization properties to dissect the data imported from databases. These parameters are also be used for inputs of Multi-Layer Perceptron (MLP) model in the simulation phase.

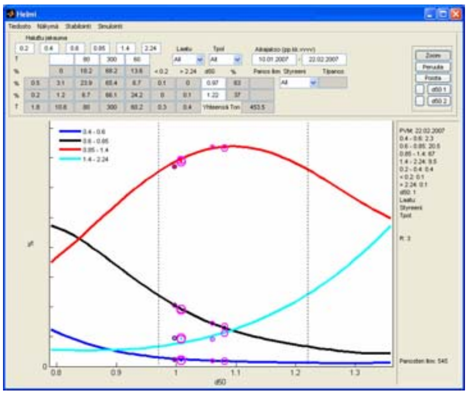

Figure 1. Interface of process optimization tool.

3.2 The tool for simulation of process parameters

The simulation tool is based on Multi-Layer Perceptron (MLP) model, which is probably the most widely used type of neural network. The tool is divided into simulation and training phases.

Training phase: Figure 2 illustrates the interface of the training phase. Data for teaching is imported automatically from databases. The user sets the basic parameters of teaching such as inputs and output variables, train rows, validation rows, test rows, amount of hidden neurons and preprocessing method. The results of the training are shown by scatter figure and indices e.g. index of agreement and correlation coefficient. The model is saved for the simulation purpose.

Simulation phase: The structure of MLP-model generates the input and output windows. Inputs are filled in automatically, if they are defined in the optimization tool. The user can simulate for example dosages of chemicals.

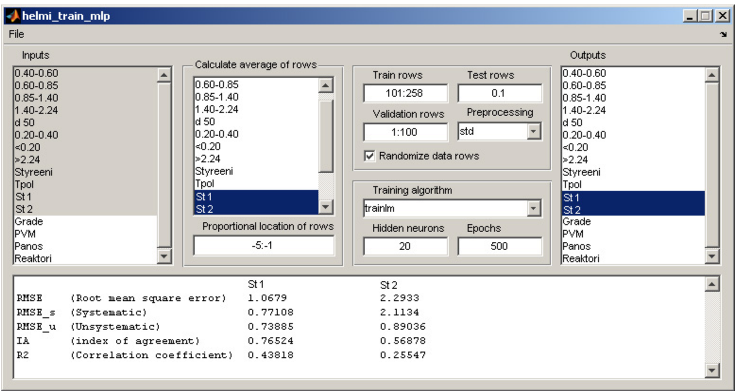

Figure 2. Interface of teaching of MLP-model

4. Summary

The present application integrates production optimization and process modeling. The results indicate that the MLP analysis provides an efficient method for data analysis in the process industry. Therefore this kind of intelligent data-driven approach is a fruitful way of developing tools for the process optimization.

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GAIN-SCHEDULING CONTROL IN SECONDARY AIR CONTROL SYSTEM

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There is a large interest in combustion of multi-fuels in Finland. Multi-fuels are usually understood as mixtures of different bio-fuels, which have a significant role in the reduction of CO_2 emissions. In some case coal and oil are burned with bio-fuels. However, the combustion of those kinds of fuels or fuel-mixtures has different properties compared to the fossil fuels (coal, gas, and oil). Bio-fuels are very inhomogeneous. The properties (heat value, moisture content, homogeneity, density, mixability) may vary in a large range. The disturbances in fuel feed are not predictable or directly measurable, only their effects on the combustion, on the flue-gas emission, on the steam generation and on the power production can be observed; e.g. through the O_2 content of the flue gas or through the variation of steam pressure, respectively. The fluctuating flue-gas oxygen-content is normally controlled by using the secondary air flows.

In the fluidized bed boiler, the hot sand bed dries and mills the fed fuel before burning in order to smooth the combustion process. The primary air is blown from the bottom of the boiler to fluidize the bed and the secondary airs are blasted above the bed. The secondary air flows are often staged in two or three levels to improve the control of the combustion process.

The studied secondary air process contains three air feeding levels (Leppäkoski et al 2004), (Leppäkoski 2006). The air flow in each air level is independently controlled by the air damper. The secondary air pressure is controlled by changing the speed of the air fan blower. The lowest air feeding level is just above the fluidized bed; the middle level is little above the lowest level; and the upper level is at the top of the boiler. All changes in the air pressure control signal and air flow control signals affect on the air pressure and the air flows. Note that the structure of the secondary air systems varies since the process is man-made and the structures might be modified.

The secondary air process control system has two purposes: *a*) to be a part of ratio control between the fuel flow and air flow, and *b*) to be a part of flue-gas oxygen-content control. The power controller or the main controller sends a signal to a calculation block, which defines the reference values to the controllers of the secondary air system and the primary air system. Timing between the fuel feeding and air feeding is essential in order to continuously maintain the correct air/fuel ratio without disturbing flue-gas oxygen-content. The fuel/air ratio control is likely performed in the best way by using the parallel fuel/air ratio control, and the relation is tried to maintain in a defined value. In flue-gas oxygen-content control, the secondary air flow controllers track the changes influenced by the flue-gas oxygen-content controller. They form a cascade loop, in which the flue-gas oxygen-content controller is the outer controller and the secondary air flow controllers are in the inner control loop.

To tune the controllers of the secondary air system a suitable process model is used. The real secondary air process is multi-variable, (almost) time-invariant system, and therefore a model-based control design method improves the quality of control design. PI controllers are normally used in the real process, and the same controller type is employed in simulations.

The secondary air system is modelled using a Hammerstein structure. The structure contains a non-linear static part followed with a linear dynamic part (Ikonen & Najim 2002). Generally, the

Wiener/Hammerstein structures may suit well in modelling chemical processes (Ikonen & Najim 2001). In this case, the static part consists of the tensor product, and it can be considered as a grey-box model made for this specific process to improve transparency and include the constraints of the process (Leppäkoski et al 2004), (Leppäkoski 2006). The linear part is a transfer function with unit gain.

Different solutions can be used to compensate non-linearity in the process (Isermann et al 1992). Gain scheduling, the use of inverse model and the continuous adaptation of control are possible approaches. In order to ensure equal operation over whole region, gain scheduling is a reasonable solution. The controllers are tuned by applying the ITAE (the integral of time and absolute error) criterion (Åström & Hägglund 1995). Gain scheduling may offers a method, which can be modified on site.

The guidance of the controllers may be conducted by employing various methods. The methods based on local learning may be considered to be suitable to guide the controllers of the secondary air system. B-spline basis functions may be used in the B-spline neural network or in the ASMOD model (Brown and Harris 1994), (Kavli, 1993). Even the use of only main control signal of each secondary air process controller in gain scheduling improves significantly the performance when comparing to the controller with fixed parameters.

The controllers can be tuned in a suitable way when the process models are realistic enough. The objective is to find the methods, which can be applied in practise. Gain scheduling guarantees better and smoother performance over the whole operation region. The better tracking of reference values in secondary air control system enables also the better tuning of flue-gas oxygen-content system. Furthermore, fault tolerant control may be useful to apply in the control system due to the possibility of malfunction of the air dampers.

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Identifiability analysis and qualitative experimental design for synthetic biological networks

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The increasing interest in using biochemical synthesis routes for producing complex fine chemicals and intermediates in the pharmaceutical industry constitutes the general motivation behind the EUROBIOSYN project. Large reaction networks are required to develop a purely enzymatic synthesis for complex molecules from simple (sugar) substrates.

One way to construct such a functional enzymatic reaction network is called a System of Bio-transformations (SBT) and is based on a selected part of one single organism's metabolic network containing the synthesis paths including cofactor regeneration reactions. Suitably modified genetic mutants of *E-coli* microorganism are used in this work to produce the metabolic network for SBT, which is performed as cell free extract in the production phase. The key product is Di-hydroxy-acetone phosphate (DHAP), and the DHAP-producing SBT contains all the enzymes for the glycolysis reactions, leading to a system of high complexity. In order to understand the system functionality and to optimize the production it is desirable to develop quantitative dynamic process models, which exhibit good long-term prediction properties over a wide range of the operating region.

During model development the important steps are assessment of identifiability of model parameters and qualitative and quantitative experimental design for model (in)-validation. Qualitative experimental design determines which input variables should be perturbed and which outputs should be measured in the experiments in order to be able to render all possible model parameters identifiable. Quantitative experimental design concerns manipulation of the inputs and the initial conditions and determination of the time to measure the outputs in order to reduce the uncertainty of the estimates of the model parameters.

Given a set of measured states the aim is to determine which parameters can be estimated. However a subsequent question is which extra states should be measured in order to render a maximum number of parameter identifiable.

In order to determine which parameters are identifiable a two-stage analysis is performed. The first stage aims at finding the identifiable reaction rates (fluxes) based on stoichiometry. In the second stage a method based on generating series is used to assess the identifiability of the parameters in the kinetic rate expressions for each of the identifiable rates.

Successively, an extra state is considered being measured and the procedure repeated until all the parameters are rendered to be identifiable or until the entire model states are considered. In addition perturbation of inputs are considered in a successive manner as well to improve parameter identifiability.

Once it has been determined which inputs are to be perturbed and which outputs should be measured, quantitative experimental design is to be performed. A criterion based on the observed Fisher information matrix is to be used to determine the input perturbations, initial conditions and to determine the time to measure the states. The presentation will focus on the identifiability analysis and qualitative experimental design for a model for the SBT for DHAP production.

Posters

Analysis of CSTR by Entropy Generation Minimization

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In recent years, efforts have been directed at improving the cost-benefit function, besides developing environmentally benign processes, based on the optimization of industrial processes. With the advent of high speed computer technology, the use of well-established numerical methods, as well as, advanced procedures such as heuristic analysis, combinatorial optimization of superstructures or finite time thermodynamics, or even the principle of equipartition of forces, have all allowed, at least in theory, the generation of noteworthy results. However, in practice, the implementation of such optimization strategies has still proved to be a challenging task.

Although the concept of entropy, the understanding of which is admittedly difficult, is still of restricted use, its application together with other thermodynamic functions seems to be the best way to reach optimal operational conditions for industrial processes. For instance, an increase in the production of by-products in the chemical reaction or the self-degradation of the main product can be related to the development of the entropy generation rate. In the case of the isolated use of the concept of energy for the optimization of such a process, it is possible that an additional spending of energy can be observed in the separation section, so that the reduction in the total consumption is not verified. Furthermore, the treatment and disposal of all or some by-products certainly will contribute to additional energy consumption.

Several researchers have devoted their time to developing an appropriate approach for process design. Combinatory optimization of superstructure, a heuristic approach and finite-time thermodynamics analysis are examples of these valuable developments. Since the classical work of Prigogine and Tolman and Fine it is well known that the maximum available work is reduced by an increase of the entropy of the system. Notable contributions on Minimum Entropy Generation have been made by Bejan and Schön and Andresen. Sauar and others have presented a process design based on the principle of equipartition of forces, which is derived from irreversible thermodynamics. Recently, an investigation into the minimum entropy generation rate in a plug flow reactor has been carried out the results of which showed a reduction of the entropy production rate, as well as, a gradient of temperature with an optimal temperature profile as a function of the reactor length.

The goal of this work is to investigate the behavior of the entropy production rate for a continuous well-stirred tank reactor (CSTR) when a chemical reaction occurs, of the type $A \rightarrow B$ of the first order, irreversible and exothermic, assuming that the reactor is homogeneous, that is, the values of physical and chemical properties are independent of the spatial distribution, which is reasonable from the practical point of view.

Based on the mass, enthalpy and entropy balances, as well as on the Gibbs-Helmholtz relationship, the following equation can be obtained:

$$\dot{\sigma} = F_e \, \rho \, c_p \left[\frac{(T_e - T)}{T} - \ln\left(\frac{T_e}{T} \right) \right] + k_0 \exp(-\frac{E}{RT}) \frac{F_e C_A^e}{k_0 \exp(\frac{-E}{RT})V + F_e} V \left(\frac{-\Delta G_0}{T_0} + \Delta H \frac{\Delta T}{TT_0} \right)$$

where $\dot{\sigma}$ means the entropy production rate per unit volume.

Since the above Equation is differentiable and considering either $d\dot{\sigma}(T)/dT = 0$ or the analysis of the behavior of the function, then, the minimization procedure can indicate the conditions for optimality, as for instance, the relation between the inlet temperature and the temperature of reaction, which applied to the set of balance equations, can determine the operating point for the system.

The results reveal the relationship between the inlet stream temperature and the reactor temperature, which is given by

$$T^e - T = -\frac{k_0 C_A^e V}{\rho_e c_p}\left\{ \Delta H\left[\frac{\exp(-E/RT)\left[(E/RT) - k_0\ \exp(-E/RT)V - F_e\right]}{\left[k_0\ \exp(-E/RT)V + F_e\right]^2}\right] - T^2\left[\left(\frac{-\Delta G_0}{T_0}\right)+\left(\frac{\Delta H}{T_0}\right)\right]\left[\frac{\exp(-E/RT)\,(E/RT^2)\,F_e}{\left[k_0\ \exp(-E/RT)V + F_e\right]^2}\right]\right\}$$

Using the data from Table 1, $(T^e - T)$ can be still graphically depicted by

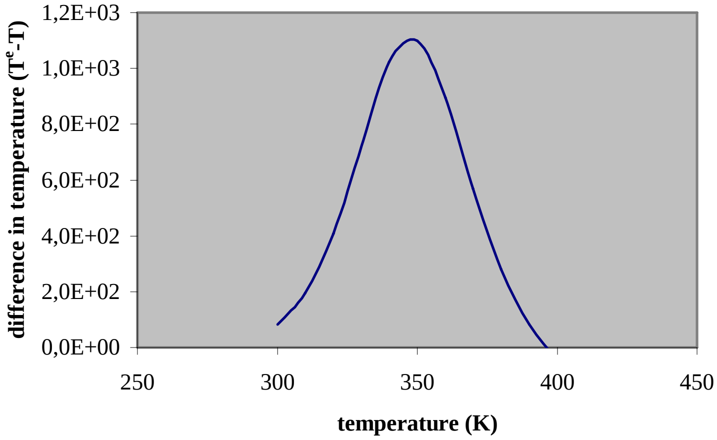

Table 1. Operating conditions and parameters for the CSTR.

Variable	Value	Variable	Value
F^e	100 L/min	E/R	8750 K
C_A^e	1 mol/L	k_0	$7.2\text{x}10^{10}$ min^{-1}
T^e	350 K	UA	$5\text{x}10^4$ J min^{-1} K^{-1}
V	100 L	T^c	300 K
ρ	1000 g/L	ΔH_f (300 K)	-52,000 J/mol
c_p	0.239 J/g K	ΔG_f (300 K)	-47,740 J/mol

Acknowledgment

The Catholic University of Pernambuco is thanked for the support.

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Volterra model based predictive control, application to a PEM fuel cell.

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I. Extended Abstract

Fuel cells technology has proven a great development in recent years, mainly in the search of efficient and less polluting alternative sources of energy to the traditional ones. There are still many open issues regarding the practical use of this technology, depending on the type of fuel cell being considered. These research topics range from manufacturing issues to materials science, and process control is among those areas of active work. In this paper, a Polymer Electrolyte Membrane (PEM) fuel cell is considered, whose fast dynamical response and low temperature operation makes it suitable for mobile applications.

Linear controller design techniques are widely employed in industry, although a great deal of processes are non-linear. In many situations the process is operating in the vicinity of a nominal operating point and therefore a linear model can provide good performance. The simplicity and the existence of tested identification techniques for linear models allows an easy and successful implementation of linear controllers in many situations. However, there exist many situations in which non-linear effects justify the need of non-linear models, such as in the case of strong non-linear processes subject to big disturbances or setpoint tracking problems where the operating point is continually changing, showing the non-linear process dynamics.

When the model is nonlinear the resulting control schemes present some challenging problems. A clear example is Linear Model Predictive Control, (MPC) which is arguably the most popular advanced control technique in industry, due to the intuitive control problem formulation and its ability to deal with economic objectives and operating constraints. However, its nonlinear formulation has a lot of open issues, and its scarce influence on industrial control practice is nowadays due to two main reasons: on one hand its online computational complexity and on the other, its inability to construct a nonlinear model on a reliable and consistent basis, despite nonlinear dynamics are significant in industrial processes.

Using a nonlinear model changes the predictive control problem from a convex quadratic program to a non-convex nonlinear problem, which is much more difficult to solve. Furthermore, in this situation there is no guarantee that the global optimum can be found, especially in real time control, when the optimum has to be obtained in a prescribed time. The solution of this problem requires the consideration (and at least a partial solution) of a nonconvex, nonlinear problem (NLP), which gives rise to a lot computational difficulties related to the expense and reliability of solving the NLP on line. Nevertheless, when the process is described by a Volterra model, efficient solutions for the model predictive control problem can be found. This solution makes use of the particular structure of the model, giving an on-line feasible solution.

The main advantage about the use of Volterra models relies in the fact that being a natural extension of the linear convolution models, they are quite straight forward to obtain from input/output data without any prior consideration about the process model structure. Hence, in this paper the ability to capture non linear dynamics of the process combined with the explicit consideration of operation constraints are taken into account.

The paper is organized as follows. First the PEM fuel cell is described, as well as the control objective. In the following section, the model prediction equations and the optimization procedure that involves the controller is presented. Then the proposed control strategy is tested under simulation of a PEM fuel cell model, where a comparison with other control techniques is performed. Finally, the major conclusions are drawn.

Potential of dry line information to the control of paper machine

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The wood fiber pulp loses water, while it is transported on the wire of the paper machine. Both a camera and the bare eye is able to observe one or more transversal, uneven lines which indicate changes of reflection or scatter of light by the pulp surface. Certain requirements are set to the homogeneity of illumination and location of the optical observer, in order to detect a dry line as the frontier line between the brighter and darker surfaces.

By recent measurements of dry lines based on the use of the scanning laser light, we have both detected dry lines and could make comparations between them and the profiles of certain properties of the final product, like formation, porosity and moisture. Use of the correlations observed for control of the corresponding profiles of the final product is submitted to a discussion.

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Balancing material and energy flows

ABSTRACT

This paper presents examples of costs formed by systematic errors in flow and energy measurements, the principle of mathematical data reconciliation and practical examples from process industry where data reconciliation is used together with field calibrations to significantly improve measurement quality.

Systematic errors of 5-10% in material and energy measurements for process industry are common. These errors raise significant costs for the industry due to incorrect control actions as well as insufficient optimisation. Cost effects are generated at every level of the automation hierarchy. Ranging from the uncertainty of custody transfer (supplier-customer) measurements to misguided investment decisions.

Modern automation and instrumentation systems are a vast source of redundant measurement information. This information – due to measurement errors – has conflicts, which can be seen as unbalances in material and energy flows. Mathematical data reconciliation provides new estimates for each of these measurements in order to fulfil balance equations. Furthermore errors in each of the measurements can be evaluated based on the relationship between the original and the estimated values.

Correcting actions can be directed to the most likely inaccurate positions based on the error estimates as well as technical and economical evaluation. As a result maintenance and calibration costs are reduced and more importantly costs due to systematic errors are minimized in all levels of automation hierarchy.

Embedded Control and Monitoring Systems in Production Machine Networks, EMPRONET

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Keywords: Performance monitoring, Fault diagnosis, Fault tolerant control

ABSTRACT
Constantly tightening competition is setting higher requirements for quality of products and overall efficiency of production plants. This can be seen as reduced personnel, higher production speeds and lower stock levels. Products are no longer manufactured into stock but just on time to fulfil the orders as this is more efficient in terms of bound capital. All these things contribute to the whole delivery chain being more vulnerable to disturbances. At the same time the amount of operating personnel is decreasing, and the production sites are becoming ever larger and more complex. This is why there is a need for new kinds of tools for managing complex production sites more efficiently.

The goal of EMPRONET (embedded control and monitoring systems in production machine networks) project is to increase the intelligence level of production machines by networking and integrating the embedded systems of the machines into larger automation system entities. These entities will use methods of condition monitoring, fault diagnosis, intelligent control, and optimization of processes and production chains. New information and communication techniques will be utilized to improve the interconnection between production machines and the control systems. This will lead to intensified use of production resources and increased competitiveness of the industry.

The novelty of the research comes from developing methods to integrate complex networked industrial systems within embedded automation middleware refining the process data and connecting the system to other process or enterprise level information systems. The automation middleware consists of condition monitoring, fault diagnosis, fault tolerant control modules, and information network.

The function of the condition monitoring modules is to supervise the performance of the process and detect anomalies in the process by using key figures representing the performance. The key figures include things like production, quality and balances of raw materials and energy. Calculations are usually based on static models.

The fault diagnosis modules are utilized to detect and isolate faults. The function of the fault detection is to find out if there are any anomalies in the operation of the process. The task of the fault isolation is to identify the faulty component, the type, and the severeness of the fault. The applied methods include quantitative and qualitative model based and process history based methods.

The results of the fault diagnosis can be utilized in the fault tolerant control if there is enough confidence in the results and the effects of the fault are known. The objective of the fault tolerant control is to make the best use of available performance after a fault situation so that losses are minimized, safety maximized, and possibly unplanned shutdown can be avoided. The methods used are accommodation of controller parameters and reconfiguration of the control structure.

In the sub-projects of Tampere University of Technology the applications so far include fault diagnosis and fault tolerant control in thermal power plants, performance monitoring and diagnosis in a pulp drying machine, and intelligent control and diagnosis of small scale woodchip combustors. In the power plant application the goal is to develop a model based fault diagnosis framework and the fault tolerant model predictive control scheme based on the structural analysis of the power plant process. For the pulp drying process a commercial application for online performance monitoring and diagnosis has been developed. The main goal was to develop a general process data history based condition monitoring system that would enable large scale commercial use by economical feasibility and usability. The system is running in a standard DCS system. With the small scale woodchip and pellet combustors the goal of the project has been to develop an intelligent control and monitoring system based on computation and process modeling instead of expensive process instrumentation (flue gas analyzers). The combustion process is modeled and the control system utilizes some low cost sensors and fuzzy logic.

EMPRONET project is a consortium of three laboratories: Laboratory of Process Control and Automation in Helsinki University of Technology, Institute of Automation and Control in Tampere University of Technology, and Systems Engineering Laboratory in Oulu University. The project is funded by the Academy of Finland and the counter parts of the industrial application projects. The duration of the EMPRONET project is 4 years ending in 2009.

A dynamic model of the paper machine short circulation process

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Extended Abstract:

The work done in this poster presents a dynamic simulator of the paper machine short circulation process.

Many important tasks are performed in the short circulation process. Dilution of the fiber suspension entering the process to a suitable consistency for the headbox takes place in the short circulation, in a mixing process where low-consistency water from the wire-pit is mixed with high-consistency stock. The second important task of the short circulation is the removal of impurities and air. This task is performed in the hydro-cyclones, machine screens and the so-called deculator. Acting as the intermediate process between stock preparation and the former, the short circulation process is very important for paper quality control, because the basic weight, ash consistency and stock jet ratio control are performed in the short circulation part. In short, retention and formation of fibers as well as drainage of water takes place in the short circulation process.

The model is based on balance equations for the fibres and the water for the different vessels in the short circulation process. The pipe flows are modeled with static equations using standard pipe flow calculation methods. The transport delays in the pipes and on the wire are modeled using Simulink's variable transport delay blocks. The model is illustrated to essentially capture the behavior of a more rigorous first-principles simulator. This poster reports some work in progress and it is our intention that the model will be used for fault detection and diagnosis purposes in the future, e.g. together with the causal digraph method. The model can furthermore be used as a tool in process control education or for dynamic control system studies.

Network of Integrated Biomeasurements and Control via Intranet and SMS

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The NIBCIS-system (Network of Integrated Biomeasurements and Control via Intranet and SMS) was developed for data acquisition, data integration and combining distributed measurements during bioreactor process monitoring. In general, it is advantageous that all data are collected *on line* at one place and shared *on line* with other applications, such as Matlab/Simulink (MathWorks) based distributed controllers. Data services, remote monitoring and control of ongoing cultivations were approached by a microcontroller-based interface module and device specific software. In addition, information delivery via SMS mobile phone was added to the system. The microcontroller (ATMEGA8535) based interface module capable of communicating with a PC using a standard serial port (RS232) was developed for devices using other than serial data interface, e.g. analogue signals. Device specific software was developed for each laboratory device integrated to the system by using Visual Basic 6.0 at Windows 2000/XP environment. The device specific software is able to communicate with the target device as required in each case. In most cases communication is done via serial port either directly or with the help of the interface module.

The technologies were developed around commercial software called MFCS (Multi Fermentor Controlling System), which is now extended to accommodate many different devices with greater ease and flexibility. Various measurement devices were connected and synchronized to an integrated system with many bioreactors. Integrated devices were for example biomass monitoring, mass spectrometer and glucose control. Data transferring to MFCS via software driver interface were developed for each integrated device. System flexibility was increased by developing a server application (mfcsServerPro) for MFCS capable of converting the software interface (MFCSAPDA) to a simple network TCP/IP interface. This implementation made it possible to share and collect *on line* data via intranet and distribute measurement devices so that they could be connected to any PC in the laboratory intranet. Currently more than ten different external laboratory devices are integrated to the system built around MFCS and eleven bioreactors. The microcontroller-based interface module proved to be a simple and inexpensive method for integrating devices with analogue interface.

Simulation of Fault Scenarios using a Paper Machine Simulator

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Extended Abstract

In order to meet the demands from industry concerning quality, efficiency and safety, numerous fault diagnosis methods have been developed. However the application of these methods in the paper industry has not been reported so much in literature.

The aim of the present research is to simulate fault scenarios on a paper machine simulator developed by VTT (Finland Research Center). The data collected from simulated fault scenarios are to be used for the evaluation of different fault diagnosis methods.

The first fault scenario is the plugging problem of the hydrocyclone in the short circulation sub-process, which will damage the hydrocyclone equipment and leave more contaminants to go to the end-product. The second fault scenario is drift problem of the consistency sensor for the stock feed line of chemical pulp, which in turn will result in the higher portion of expensive fibers in the mixed pulp and less economical efficiency of the plant. The third fault scenario is a retention drop on the wire section, which means weak transportability of the fibers from stock to end-product. The responses of the plant for these four different fault scenarios are present and discussed in this paper.

Design, development and testing of an online process monitoring system

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ABSTRACT

The process industry is constantly evolving. Globalization, product safety, quality issues, tighter environmental and chemical laws and financial issues create constant pressure to get more out of processes and process control. Process monitoring systems are operator support systems for process control, enabling the prediction of process disturbances and optimizing the process conditions. Financial benefit is achieved with better product quality and fewer product failures.

In this research software was programmed for the purpose of monitoring and process data analysis. The software enables the creation of different monitoring models, such as principal component analysis and partial least squares. In addition, an online Add-in for the Proscon ACT process control software used at Outokumpu Technology was developed for real-time use.

The paper describes the development steps of an online process monitoring software. The steps include the definition of the application, data preprocessing, selection of variables, the usage of calculated, nonlinear process variables, teaching of the model, testing and online implementation.

The functionality of the software was tested on the experimental data from the Outokumpu Chrome’s Kemi mine.

Full Papers

PHYSICAL MODELING, ANALYSIS AND ACTIVE MODEL-BASED CONTROL OF ROTOR VIBRATIONS IN ELECTRIC MOTORS

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Abstract: Active control of rotor vibrations in electrical machines is considered. The objective is to diminish unwanted forces generated by rotation and unbalanced mass of the rotor. These forces, dependent of rotational speed, cause vibration that, when occurring in the natural frequency of the rotor, cause severe problems. Extra windings were built in the stator of the machine, and they are fed with frequency converter to create an opposite force to the vibration. The main task was to develop a controller for the system. The system was first modeled by electromechanical equations, and from FEM simulations more simplified state-space-models were identified. The rotation speed of the motor is limited by the critical frequency that depends on the size and weight of the rotor.

Keywords: Electrical machines, rotor dynamics, electromechanical modelling, vibration control, active control, model-based control, LQG control, convergent control.

1. INTRODUCTION

Vibration control of different engineering applications is growing all the time, as the precision and accuracy demands for different engineering solutions are getting more stringent (Rao, 2000). As the allowed tolerances become smaller, the vibrations have a bigger impact on the total system. For example, air-gaps in electric drives need to be smaller to increase the overall efficiency of the machine, yet the vibrations hinder this goal as the air-gap varies along to the vibrations (Chiasson, 2005). Passive damping has been widely used for many different applications, but it can only be used to dampen vibrations at a certain frequency (Inman, 2006). In high-performance control passive damping is then inadequate and an active control method is needed. In active control an external force is excited to the system according to a control law with the goal to minimize the vibrations. Active control is becoming more and more important all the time, and new research efforts are introduced into this field. It can be designed with traditional control methods to a certain extent, but the harmonics of the main vibration frequencies and the dynamic nature of the load disturbance may need more sophisticated control methods (Tammi, 2007, Daley *et al.* 2006).

In this paper active control of rotor vibrations in electrical motors is considered. The driving speed of the motor is limited by the critical frequency that depends on the size and weight of the rotor. An all purpose motor would bring savings for the manufacturing company and the customer as the motor doesn't have to be designed for a certain operation condition only. Specifications for any application to be designed also become simplified as all the drive speeds are available instead of just a single speed.

The idea in the vibration controls to be introduced is to generate a control force to the rotor through extra windings in the stator. This actuator generates a magnetic field that induces a force negating the disturbance force exited by the mass imbalance of the rotor. A similar approach has been used earlier by Chiba *et al.* (1991), who constructed a two-pole winding to a four-pole induction motor.

The modeling process is initialized by the first principles of electromechanical systems, see e.g.

Chiasson (2005). A separate electric model is created for the actuator generating control force with a magnetic field. An electromechanical model is then formed for the rotor that transfers the input forces into displacements. In addition to the physical model of the system a FEM-model is created to help in the validation of the results, and to generate black box data (Arkkio, 1987). The next phase is to manipulate the physical models in such way that they become standard transfer-function matrices. Alternatively, an augmented state-space representation that includes the actuator, disturbance and rotor models in a single composed model can be used. The state-space representation is constructed by selecting the state-variables from the physical model that yields an exact model of the system with some couplings between inputs. The other approach is to identify the system from the data achieved from FEM-simulations, which describe the system behavior very accurately. By identification the model can be simplified such that the couplings between inputs disappear, but the model still describes the system well enough. When the reduced model is ready, it is validated by simulations against the FEM-model. The FEM-model is very slow to simulate, so a Simulink-model with approximately the same behavior is needed.

Three different modern control methods will be tested to dampen the vibrations. An LQ controller with integration added is first tried in order to dampen the sinusoidal disturbance caused by the unbalanced rotor. Secondly, an LQ controller operating together with the so-called convergent control algorithm is tested (Daley *et al.* 2006). Finally, a similar idea with a nonlinear controller in place of the convergent control algorithm is designed.

All control designs achieved for the system are tested and validated by using the FEM process model. A control loop with controller tested in Simulink is included in the FEM-model and simulated. In order for the control models to be reliable they must have similar behavior in FEM-environment as they did in Simulink.

2. PROCESS MODEL

The process in control configuration is shown in Fig. 1. A 30 kW two-pole induction motor is studied, and a dynamic model starting from the electromechanical first principles equations has been built. An extra actuator for suppressing the rotor vibration (first mode at 49.5 Hz) has been constructed and modelled similarly. The new actuator is driven by a separate frequency converter. The rotor unbalance force can be modelled by a two-dimensional (x and y directions) input entering in the rotor model input. The rotor model is a generalized form of the basic Jeffcott-rotor model. The actuator model can be expressed in the form (1) and the rotor model in the form (2), which together can be changed into a general LTI state-space form; for details see (Laiho *et al.* 2007).

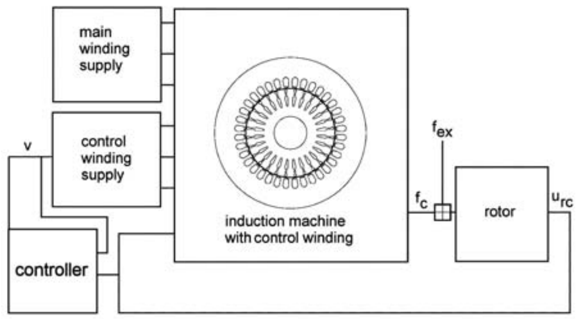

Fig.1. Process control schema: A built-in actuator inserted in the stator slots of the electric machine creates a counterforce on the rotor.

$$\begin{aligned}\frac{di}{dt} &= A_{em}i + B_{em}v + S_{em}\dot{u}_{rc} + Q_{em}u_{rc} \\ f_c &= C_{em}i + P_{em}u_{rc}\end{aligned} \tag{1}$$

$$\begin{aligned}\ddot{\eta} + 2\Sigma\Omega\dot{\eta} + \Omega^2\eta &= \Phi_{rc}^T f_c + \Phi_{rc}^T f_{ex} \\ u_{rc} &= \Phi_{rc}\eta\end{aligned} \tag{2}$$

In equation (1) the vector i contains currents in the rotor and stator, v the control voltages (two-dimensional), u_{rc} the rotor center position and f_c the control force generated to the rotor. In the mechanical model equation (2) the term η is the modal coordinate vector, f_{ex} is the disturbance force, and the matrices Φ_{rc}, Σ, Ω matrices related to the generalized eigenfrequencies and damping coefficients of the rotor.

3. IDENTIFICATION

The identification data was created by feeding pseudo random signals limited to ±1V into the control winding of the FEM-model. Pseudo random signal was chosen because of its properties. The signal can be limited to desired range; while the randomness guarantees that the whole frequency range is being used making the signal rich enough to identification purposes.

It turned out that the actuator is also highly dependent on the displacement of the rotor. Therefore more inputs had to be added to the model. The signals for the feedback were generated by using the existing rotor model in such way that the forces generated by the actuator were fed into the rotor model generating the displacement, which is then fed back to the actuator. These inputs had to be generated by the model, because the noise signals as input were very ill-behaving, which is most likely due to the stiffness of the system (fast and slow dynamics occur in the system simultaneously). However the displacement given by the rotor model wasn't rich enough as it contained only certain frequencies, and it thus generated a linear relationship between the input and output of the model to be identified. The solution for this kind of problem is to modulate the rotor displacement by another pseudo random signal limited to 10% of the output of the rotor model. This leads to situation where the displacement has low frequency behavior suitable for the actuator model, yet the noise modulation guarantees that the inputs and outputs of the system are no longer linearly dependent and the system can be identified.

The force generated by the actuator with certain inputs were acquired as the output of the model to be identified (Figs. 2-4).

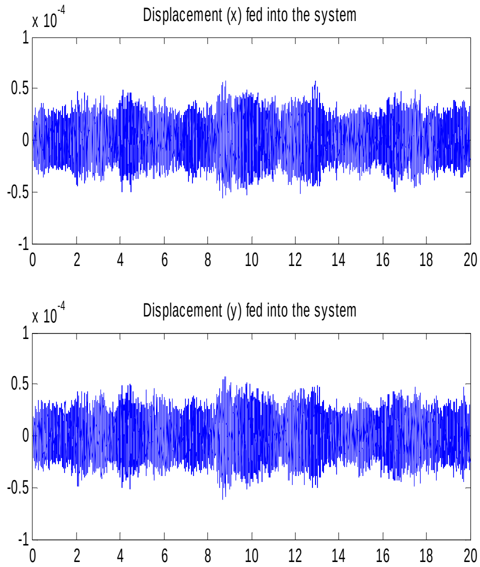

Fig. 2 Displacement input used in identification. Time is in seconds.

The sampling frequency for the data was chosen to be 1 kHz. This frequency is fast enough to catch most of the fast dynamics of the system, yet slow enough to prevent the system from becoming an integrator .

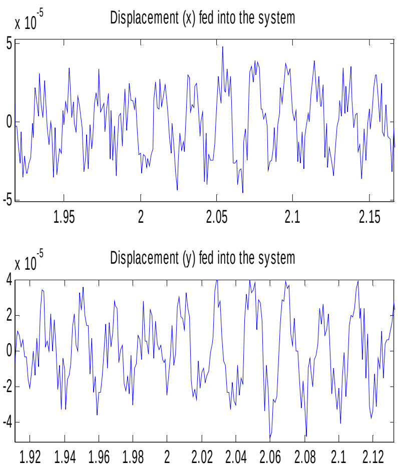

Fig. 3 Zoom-in of the displacement input

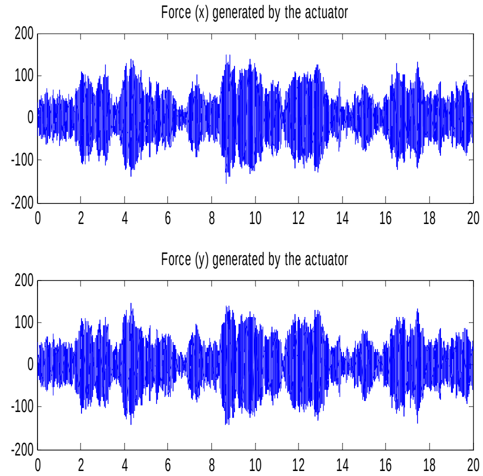

Fig. 4 Force output of the model to be identified

The input was limited to approx. 10% of the theoretical maximum, because the system is somewhat non-linear and the chance for saturation and biased model increases with the amplitudes of the inputs.

3.1 *Identification process*

At first the data acquired was divided into modeling and validation parts. The data was split in two at the middle of the data set. Another approach would have been to take every other sample to different data sets. This however wouldn't have been an ideal choice in this case as the system is highly dependent on the earlier states and taking out every second sample would have corrupted the data. The first 16 samples were removed from each data due to transient error that doesn't belong to the actual model.

The model was identified in two different phases to enhance the performance of the algorithm; instead of finding a model that generates both the outputs from the four given inputs the model was split in two in such way that separate models for each of the outputs.

The identification of the model was done by using PEM-algorithm for a 5-dimensional state-space representation. The algorithm makes an initial guess for the model and iteratively changes the model parameters. The model performance is compared against the validation data in each iteration. 5-dimensional model turned out to give the best performance ratio with respect to the number of states in the model.

3.2 *Model composition*

When separate models for both of the force outputs have been generated, the complete actuator model has to be formed. This is simply done by composing the two different state-space representations into a single one. The discrete model identified earlier will also be translated into a continuous time model. This yields a

10-state state-space model with four inputs and 2 outputs.

3.3 *Process composition*

In order to validate the model a general model of the process has to be made. The complete process includes the actuator, rotor and the disturbance. For analyzing purposes a model that includes all of the sub-models will be made. For model comparison the disturbance model is left out and only the actuator dynamics with feedback from the rotor output is considered. In the latter model the inputs are voltage and disturbance in x- and y-directions, and the output is the displacement.

In the following equations (3) and (4) the sub-indexes define, which sub-model is being used, r is for rotor, a is for actuator, d stands for disturbance, 1 is the voltage part of the actuator's B-matrix and 2 is the displacement part of the actuator's B-matrix.

After composition the following models will be obtained for the complete process and for the process that has disturbance as input.

$$\begin{cases} \dot{x}(t)=\left[\begin{array}{c|c|c} A_r & B_rC_a & B_rC_d \\ \hline B_2C_r & A_a & 0 \\ \hline 0 & 0 & A_d \end{array}\right]x(t)+\left[\begin{array}{c} 0 \\ \hline B_1 \\ \hline 0 \end{array}\right]u(t) \\ y(t)=\left[\begin{array}{c|c|c} C_r & 0 & 0 \end{array}\right]x(t) \end{cases} \qquad (3)$$

$$\begin{cases} \dot{x}(t)=\left[\begin{array}{c|c} A_r & B_rC_a \\ \hline B_2C_r & A_a \end{array}\right]x(t)+\left[\begin{array}{c|c} 0 & B_r \\ \hline B_1 & 0 \\ \hline 0 & 0 \end{array}\right]u(t) \\ y(t)=\left[\begin{array}{c|c} C_r & 0 \end{array}\right]x(t) \end{cases} \qquad (4)$$

3.4 *Model validation*

In order to find out whether the identified model is accurate enough, validation must be made. Because there is another model for the rotor-actuator system available (generated by subspace identification), cross-validation will be used to find out the true performance of the model.

In the cross validation all the input-output data available will be used. One of the data sets was used to identify this model and the other was used to identify the other model. Now it is easy to determine, which of the two models is more accurate to the given system. The validation will be made both in time-domain and frequency domain. In frequency domain the true frequency response of the system is available and the comparison will be made against it.

The frequency domain comparison can be seen in (Figs. 5-8).

For the future reference the model identified in this paper will be called PEM and the model that is used for cross-validation will be called SUB. The models were compared to those obtained by FCSMEK, which is a program developed to do accurate FEM –based calculations on the behaviour of the electric machine.

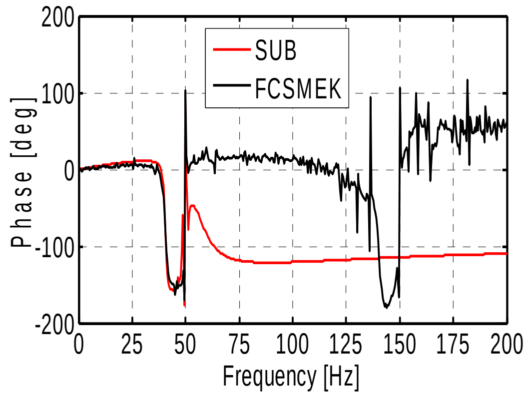

Fig. 5 Phase plot of the SUB-model

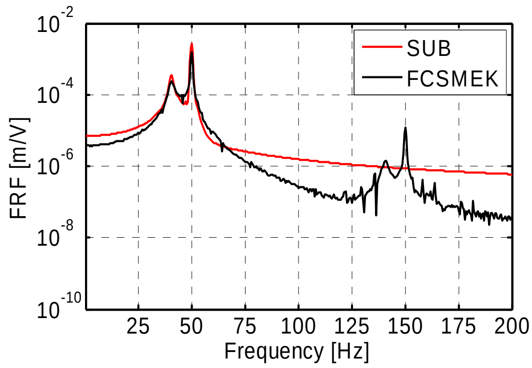

Fig. 6 Gain plot of the SUB-model

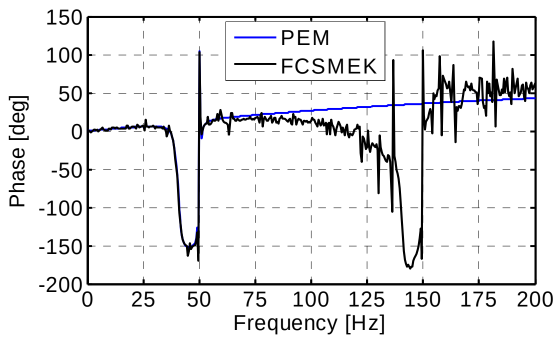

Fig. 7 Phase plot of the PEM-model

The frequency-domain comparison gave some hints that the PEM-model could be more accurate. In order to verify this, time-domain cross-validation is made (Figs 9-11).

Unfortunately due to the different identification methods, the data to cross validate the complete PEM-system with PEM data or complete SUB-system with PEM-data were not available.

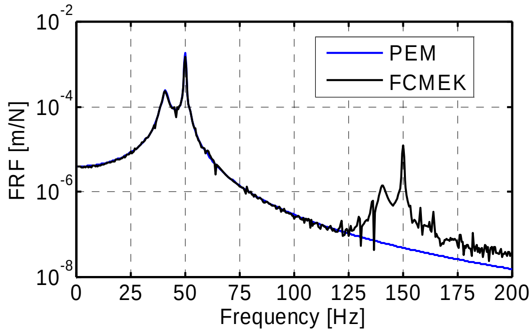

Fig. 8 Gain plot of the PEM-model

However it's clear that the PEM model works better with both the original PEM identification data and the complete PEM-system against SUB identification data.

According to both of the frequency- and time-domain comparison the PEM model is clearly more accurate and more well behaving than the SUB model.

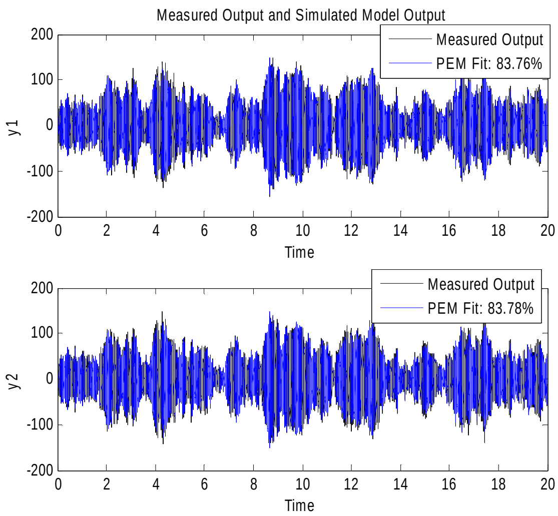

Fig. 9 PEM-actuator only with PEM data

4. CONTROL

At first a regular LQ-controller with integrator added was implemented for the system. Rotor output, rotor displacement, was emphasized in the weighting matrix. A classical state estimator was constructed to observe the states (Glad and Ljung, 2000). With a proper tuning the controller performs well, as shown in Fig. 12. The initial period of 0.5 s (without control) was used in order to settle down the initial transients on FCSMEK (FEM) simulation. The rotor vibration reduced considerably, after the controller had been switched on. Also the control signal performed well producing only about 0.2 V control input on the rotor.

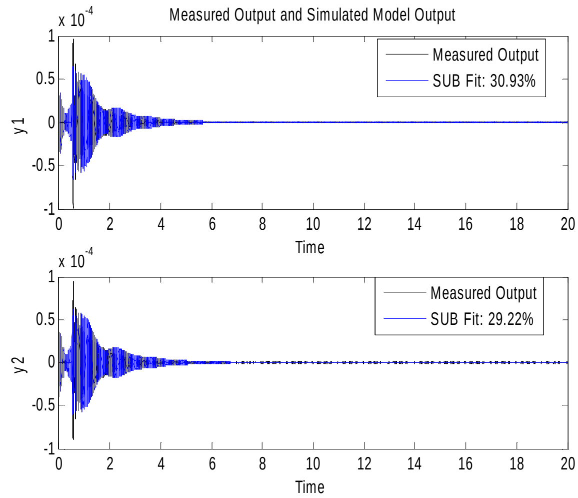

Fig. 10 SUB-complete model with SUB-data

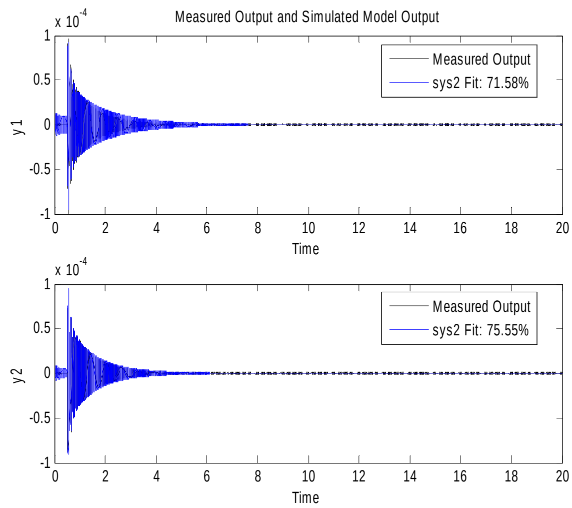

Fig. 11 PEM-complete with SUB-data

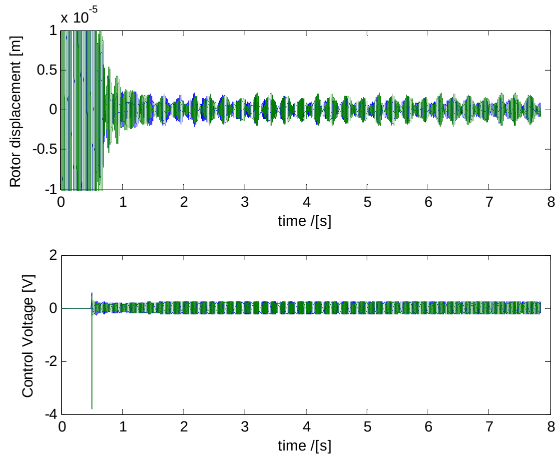

Fig. 12 Process controlled with an LQ controller

A more advanced control strategy was then tried (Fig. 13). It consisted of a standard LQ controller used to reduce the resonance peak and shift it in the frequency domain (the actuator resonance frequency 49.5 Hz is very near to the critical speed 50 Hz), and the convergent control algorithm to suppress the rotor vibrations. For details on convergent control, see e.g. (Daley *et al.* 2006). In this experiment the algorithm did not work properly. A modified version (Figs. 14-15) worked better, but still worse than the

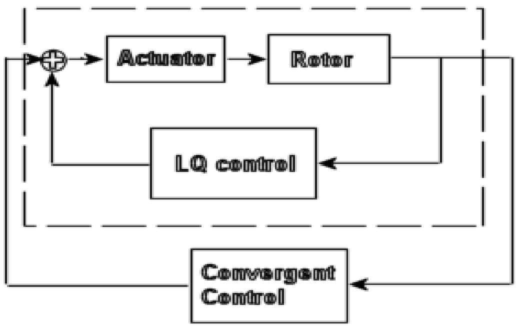

Fig. 13 Control schema of LQ control combined with convergent control.

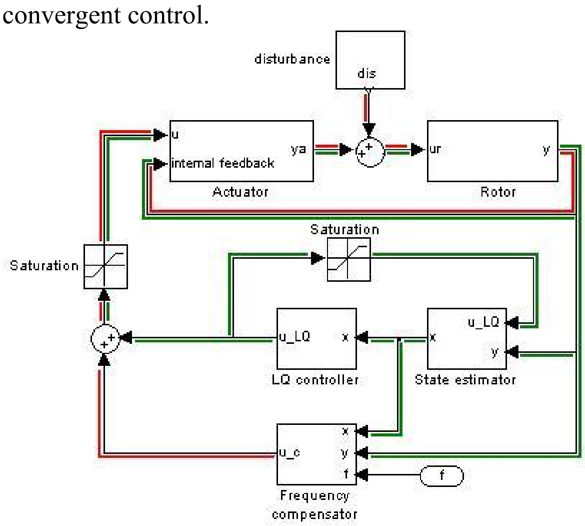

Fig. 14 Modified LQ and convergent control structure

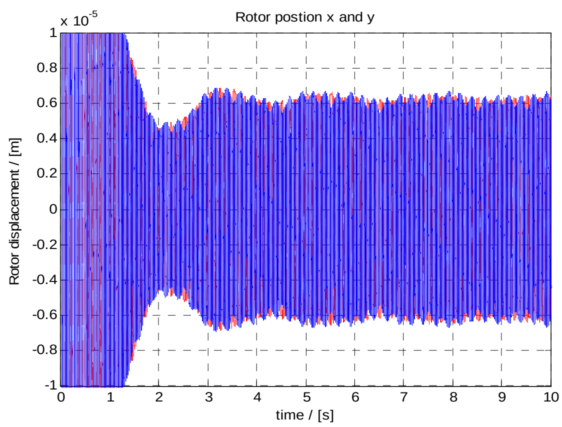

Fig 15 Vibration control result when the modified control structure was used

original LQ controller. It should be emphasized however that at the moment of writing the research is still going on, and more mature results are still to come. The final testbench is a real test machine, which is currently under construction.

5. CONCLUSION

Model-based control was used to suppress rotor vibrations occurring in the critical speed of an electric machine. Starting from first principle dynamic equations for both the rotor and the new control actuator were formed. By using data obtained by an accurate FEM simulation the model parameters were estimated, and different advanced control algorithms were tested. The results were promising, although the research is still in an early phase.

ACKNOWLEDGEMENTS

The research has been financed by the Academy of Finland through the research project “Active Control of Rotor Vibrations in Electric Machines”, ACRVEM. This support is highly appreciated.

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CONTROLLED VARIABLES SELECTION FOR A BIOLOGICAL WASTEWATER TREATMENT PROCESS

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Abstract: This paper considers control structure selection for a biological wastewater treatment process, with emphasis on identifying controlled variables that contribute to minimize economic costs. This is achieved according to the self-optimizing procedure proposed by Skogestad (2000). The aim is to demonstrate how, with simple considerations on the control structure design, the efficiency of a wastewater treatment plant can be improved, minimizing operational costs in the plant, while keeping it running optimally and satisfying the effluent requirements.

Based on paper presented at the 8th International Symposium on Dynamics and Control of Process Systems, June 6-8th 2007, Cancun, Mexico

Keywords: Self-optimizing control, Cost function, Activated sludge

1. INTRODUCTION

In the last decades, environmental water protection has gained an increasing public awareness, which is also reflected in more strict effluent concentration requirements and regulations. This has, in turn, considerably increased the necessity of efficient and reliable Waste Water Treatment Plants (WWTPs) that have to face an important challenge arising from both regulation fulfillment and cost aspect of plant operation. These regulations hence give rise to both technical and economical problems since most of the existing plants have to undertake major upgrading, particularly for nutrient removals. In addition to plant improvements attained through the adoption of new equipment technologies, the application of careful considerations on control systems is required to achieve the improved benefits in practice. In particular, since inside a biological WWTP, the Activated Sludge Process (ASP) is the most common used technology to remove organic pollutant from wastewater, we focus our attention on this process.

In the literature, ASP optimization has been studied by several authors in different ways. For instance, Gillot *et al.* (1999) defined an objective cost function in order to standardize the cost calculation procedure integrating both investment, fixed and variable operating costs. Chachuat *et al.* (2001) investigate the optimal sequence of aeration and non-aeration time for a small ASP. Vanrolleghem and Gillot (2002) proposed an economic index including weighted investment and operating costs used to evaluate the transferability of control strategies to different situations. A methodology to estimate costs and benefits of online control for WWTP is developed by Devisscher *et al.* (2006). Samuelsson *et al.* (2005) and lately Samuelsson *et al.* (2007) chose optimal setpoints

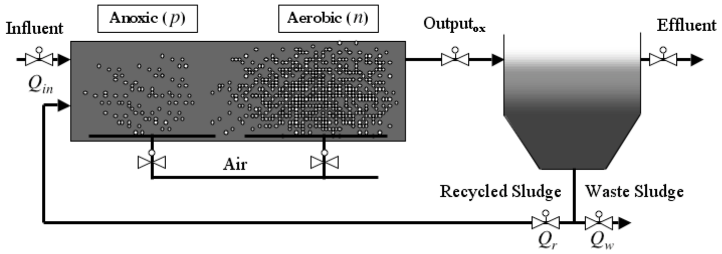

Fig. 1. Schematic representation of an activated sludge plant, with spotlight on manipulable variables.

and cost minimization control strategies only for the denitrification process, by means of operating maps. Stare *et al.* (2007) tested and compared with predictive control, various control strategies that produce optimal performance regarding operating costs and yield satisfactory nutrient removal.

In this work, it is shown how optimal operation can be achieved in practice by designing the control structure appropriately. In other words the constrained optimization problem is translated into the proper operation in the ASP process. Controlled variables are the important link between layers in the hierarchic control structure and there are many issue involved. First, we should control the active constraints (which are optimal from an economic point of view in terms of minimizing the cost). Second, we need to find controlled variables associated with the unconstrained degrees of freedom. This is the issue of self-optimizing control. We are looking for the controlled variables for the ASP which when kept constant, indirectly achieves optimal operation in spite of disturbances. In order to trade them off against each other in a systematic manner we follow the control structure design proposed in (Skogestad, 2000).

2. ACTIVATED SLUDGE PROCESS

We consider the ASP in the TecnoCasic WWTP located in Cagliari (Italy), reported in (Mulas, 2006), and schematically represented in Figure 1. Here, the bioreactor consists of an anoxic (predenitrification, p in the following) followed by an aerobic (nitrification, n in the following) zone. To maintain the microbiological population, the sludge from the settler is recirculated into the anoxic basin, while the sludge concentration is kept constant by means of sludge withdrawn from the settler.

The ASP layout has the following characteristic features:

- Biological treatment reactor (2000 m^3), with an anoxic zone followed by an aerobic zone. The aeration is obtained with fine pore air diffusers located at the bioreactor bottom. A Dissolved Oxygen (DO) controller maintains the oxygen concentration at 0.09 gO_2/m^3, in the anoxic zone and at 4 gO_2/m^3, in the aerobic one.
- Non-reactive secondary settler with a surface of 707 m^2 and 4 m depth.
- Recycled flow, Q_r, from the secondary settler to the front end of the plant at a constant flow rate of 7000 m^3/d.
- Waste flow, Q_w, intermittently pumped from the secondary settler underflow.

Furthermore, the average influent conditions for the considered plant are reported in Table 1.

The bioreactor is represented by means of the Activated Sludge Model No. 1 (Henze *et al.*, 1987), while the secondary settler representation is obtained with the Takàcs model (Takacs *et al.*, 1991); these models are coupled together in a Matlab/Simulink (R14) environment. Furthermore, in order to take into account the not ideal fluodynamic in the ASP, the biological reactor is formed with six different zones: three anoxic which represent 1/3 of the total volume and three aerated zones, corresponding to the remaining volume.

3. OPERATIONAL OBJECTIVES

In order to run a WWTP economically, costs such as pumping energy and aeration energy should be minimized; nevertheless, the discharge concentrations to recipients should be kept at acceptable level. Hence, the operational objectives includes not only the cost function to be minimized but also the constraints at which it is subjected and the disturbances that may occur in the plant.

3.1 Cost Function

Economically speaking, the overall cost in a wastewater treatment plant is highly dependent on the wastewater system itself and it can be divided into manpower, energy, maintenance, chemical sludge treatment and disposal evaluated on a time basis. Therefore, an inventory has to be made of the different costs so that individual importance

Influent Flow rate	Q_{in}	=	6152	$[m^3/d]$
Influent Chemical Oxygen Demand	COD^{in}	=	221	$[gCOD/m^3]$
Influent Total Suspended Solids	TSS^{in}	=	46	$[gSS/m^3]$
Influent Nitrate	S_{NO}^{in}	=	0.22	$[gN/m^3]$
Influent Total Kjeldhal Nitrogen	TKN^{in}	=	22	$[gN/m^3]$
Influent Ammonia/TKN ratio	f_{NH}^{in}	=	0.36	−

Table 1. Influent nominal conditions for the considered plant.

of each term is determined. In this work, the following partial costs are considered:

- Pumping costs due to the required pumping energy (E_P expressed in kWh/d);
- Pumping costs due to the required aeration energy (E_A expressed in kWh/d);
- Sludge disposal costs (C_D expressed in €$/d$).

In order, to express the partial costs we adopt the expression proposed in the COST Benchmark (Copp, 2000). Assuming a constant energy price $k_E = 0.09$ €$/kWh$ and a sludge disposal price $k_D = 80$ €$/tonn$, the total cost, J in €$/day$, during a representing time interval T can be calculated as:

$$\begin{aligned} J &= k_E(E_P + E_A) + C_D \\ &= \frac{1}{T}\Big(\int_{t_0}^{t_0+T} (k_E(0.04(Q_r(t) + Q_w(t)) \\ &+ 24\sum_{i=1}^{n}(0.4032k_{la,i}^2(t) + 7.8408k_{la,i}(t))) \\ &+ k_D TSS_w(t)Q_w(t))dt\Big) \end{aligned} \tag{1}$$

where, for a given time interval T, the first term within the integral represents E_P, the second E_A (with k_{la} expressed in h^{-1} for each reactor zone i) and the third is C_D.

3.2 Constraints

The cost in Equation 1 should be minized subject to some constraints related to process operability and regulation restriction for the effluent, see Table 2.

In terms of *operational constraints* we can identify the DO concentration in both aerobic and anoxic zones. In the aerobic zone, DO concentration should be sufficient for the microorganisms involved in nitrification reactions. It is a good practice to maintain the DO level between 1.5 and 4 gO_2/m^3, as a further increase does not improve operation, but increases aeration costs considerably. On the other hand, in the anoxic zone a lower aeration is needed in order to satisfy only the mixing requirements.

Furthermore, we know that the nitrate consumption in the last predenitrification zone ($S_{NO}^{p,3}$) should be between 1 and 3 gN/m^3 when internal recirculation is present (Olsson *et al.*, 2005), which is not the case in the considered plant. We verified that $S_{NO}^{p,3}$ between 0.75 and 1 gN/m^3 can assure a good behavior in the anoxic zone. This awards to not excessive air consumption in the aeration zones.

Operational Constraints					
0.05	≤	DO^p	≤	0.5	$[gO_2/m^3]$
1.5	≤	DO^n	≤	4	$[gO_2/m^3]$
0.05	≤	F/M	≤	1	$[gCOD/gSS/d]$
0.75	≤	$S_{NO}^{p,3}$	≤	1	$[gN/m^3]$
Effluent Constraints					
		COD^{eff}	≤	125	$[gCOD/m^3]$
		TSS^{eff}	≤	35	$[gSS/m^3]$
		TN^{eff}	≤	18	$[gSS/m^3]$
		S_{NH}^{eff}	≤	0.6	$[gN/m^3]$
		S_{NO}^{eff}	≤	10	$[gN/m^3]$

Table 2. Constraints.

In addition, the constraints related to the optimal operation of the secondary settler have to be considered. It is also important to prevent the loss of sludge solids in the effluent in order to guarantee the required degree of treatment. Hence, we consider an index that is able to represent the sludge behavior such as the Food to Microorganisms ratio (F/M). According to the literature (Meltcalf and Eddy, 1991), it must not exceed certain level as summarized in Table 2.

3.3 Disturbances

One of the major reasons for control is the presence of disturbances, and compared to most other process industries a wastewater treatment plant is subject to very large disturbances. In order to give a representation of the system behavior when disturbances occur, the nominal average circumstances are augmented by 20% (Table 3).

Two different situations are considered. The case with constant influent flow rate Q_{in} (d_1, d_2, d_3), from a practical point of view, it may happen if there is a large equalization basin before the ASP. For disturbances d_4, d_5 and d_6 also a 20% change in Q_{in} is included.

4. MANIPULATED VARIABLES AND DEGREES OF FREEDOM

In order to define the number of Degrees Of Freedom (DOF) for optimization, N_{opt}, we must identify the number of degrees of freedom for control,

Constant Q_{in}		Variable Q_{in}		
d_1:	COD^{in} + 20%	d_4:	Q_{in}, COD^{in}	+20%
d_2:	TKN^{in} + 20%	d_5:	Q_{in}, TKN^{in}	+20%
d_3:	TKN^{in}, COD^{in} +20%	d_6:	Q_{in}, COD^{in}, TKN^{in}	+20%

Table 3. Disturbances.

N_m. If we look at the schematic representation of that plant in Figure 1, we note that there are only few variables that we can manipulate; this is quite common in a biological wastewater treatment plant, (Olsson and Newell, 2002). However, there is potential to make a better use of the existing manipulated variables.

From Figure 1, we observe that there are 7 valves, but we identify only 4 degrees of freedom for control because the levels in the aeration tank and in the secondary settler need to be controlled at constant values (they are actually self-regulating) and because the influent flow rate is a disturbance and not a manipulated variable. It should be noted that inventory of sludge in the secondary settler should be controlled, but since the inventory has a steady-state effect, this does not affect the number of degrees of freedom.

As mentioned, the optimization is generally subject to several constraints. We assume that the DO concentration in both anoxic and aerobic zones are constant at the setpoint values by the airflow controllers meaning that we have two remaining degrees of freedom.

As discussed for the disturbances, two different cases can be considered. In fact, we notice that if there is not disturbance in the influent flow rate, Q_r might be considered constant: there is only one variable left for optimization. In the case where also disturbances in Q_{in} are considered, fixing Q_r/Q_{in} is a good policy, which is the is common practice in most wastewater treatment plant. In this case there are two remaining DOF.

5. OPTIMIZATION PROCEDURE AND CANDIDATE CONTROLLED VARIABLES

As the beginning of the optimization procedure, we examine the existing operating conditions for the considered plant and we notice that aeration is responsible for 99% of the total cost. Therefore, the first attention focuses on the pumping cost for the aeration and on the DO controller present in the WWTP. A preliminary optimization was carried out to find the setpoint values for the DO concentration in both controlled anoxic and aerobic zones. The results are reported as "improved" in Table 4 and we can observe a remarkable cost reduction with respect to the existing initial condition.

		Initial	Improved (Nominal)
$DO^{p,sp}$	$[gO_2/m^3]$	0.09	0.22
$DO^{n,sp}$	$[gO_2/m^3]$	4	2.5
Q_r/Q_{in}	$[-]$	1.14	1.49
Q_w	$[m^3/d]$	60	77
Cost	[€/d]	2200	1466

Table 4. Steady-state operation before and after the preliminary optimization.

Now, we can go a step further in the self-optimizing procedure and propose the candidate controlled variables. According to Skogestad (2000), these should be easy to measure and control, but sensitive to changes in the manipulated variables and their optimal value should be insensitive to disturbances. The following candidates are suggested:

- Sludge Retention Time, SRT $[d]$;
- Food to Microorganisms ratio, F/M $[gCOD/gSS/d]$;
- Effluent ammonia, $S_{NH}^{eff}[gN/m^3]$;
- Mixed Liquor Suspended Solids, MLSS $[gSS/m^3]$;
- Nitrate in the last anoxic zone, $S_{NO}^{p,3}[gN/m^3]$.

The used setpoint values for these variables (Table 5) are the average of various operation points.

SRT^{sp}	F/M^{sp}	$S_{NH}^{eff,sp}$	$MLSS^{sp}$	$S_{NO}^{p3,sp}$
9.77	0.74	0.17	1482	0.78

Table 5. Setpoint values used for the candidate controlled variables.

In Table 6, all considered control configurations are reported with the associated minimum singular value. The controlled variable sets corresponding to the larger minimum singular value ($\underline{\sigma}$) are preferred. From these, we remark that the configurations from c_5 to c_{14} take into account Q_r/Q_{in} and Q_w as inputs which means that two controller loops are involved. Configurations from c_1 to c_4 consider the recycle ratio fixed at the optimum, assuming this is a good self-optimizing variable, and the SRT, F/M, S_{NH}^{eff} and MLSS controlled by Q_w. We note that the best configurations with a large minimum singular value are c_1^2 and c_4^2 which are made fixing Q_r/Q_{in}. We then expect that those configurations are the best also in an economic point of view, but for sake of completeness, we investigate also c_8^2 and c_{14}^2. In this case, the acceptable loop pairing leads to the following control configurations:

- control SRT (or MLSS) by manipulating Q_w;
- control the nitrate concentration in the last anoxic zone, $S_{NO}^{p,3}$, by manipulating the ratio Q_r/Q_{in}.

	Configuration	$\underline{\sigma}$
c_1^2	$(Q_r/Q_{in})^{const}$-SRT	**6.50**
c_2	$(Q_r/Q_{in})^{const}$-F/M	1.004
c_3	$(Q_r/Q_{in})^{const}$-S_{NH}^{eff}	1.338
c_4	$(Q_r/Q_{in})^{const}$-MLSS	**32.20**
c_5^2	SRT-F/M	0.13
c_6	SRT-S_{NH}^{eff}	1.00
c_7	SRT-MLSS	0.83
c_8	SRT-$S_{NO_f}^{p,3}$	**1.49**
c_9	F/M-S_{NH}^{eff}	0.76
c_{10}	F/M-MLSS	0.00
c_{11}	F/M-$S_{NO}^{p,3}$	0.86
c_{12}	S_{NH}^{eff}-MLSS	1.14
c_{13}	S_{NH}^{eff}-$S_{NO}^{p,3}$	1.02
c_{14}	MLSS-$S_{NO}^{p,3}$	**1.41**

Table 6. Minimum singular value for the proposed configurations.

We note that the candidate controlled variables involve SRT and MLSS. We know that keeping the SRT a constant setpoint value implies to hold the nitrification capacity of the sludge (measure of the maximum nitrification rate) at a constant level, and especially when the flow rate and load are not constant this should be allowed to develop in the system as a result of an increase influent (Olsson *et al.*, 2005). Also for this reason, we expect that the configurations regarding mixed liquor suspended solid measurements will be preferable.

6. CONTROLLED VARIABLES SELECTION

We here consider in detail the actual cost for the considered configurations. From Table 7, it is clear that for disturbances d_1, d_2, and d_3 that the cost is considerably reduced and that it is possible to obtain further saving if a MLSS controller is implemented in the ASP.

Also when the influent flow rate is not constant (d_4, d_5, and d_6), the best way to operate is to fix the ratio Q_r/Q_{in} and control the MLSS concentrations by means of the waste flow rate Q_w. It follows that the recycled sludge pump will change Q_r on the basis of influent flow rate measurements, assuring an appropriate amount of biomass in the system.

In both situations, with and without flow rate disturbances the adjustment of waste activated sludge flow is based on MLSS measurements and on the ratio between the recycled sludge and the influent flow rate, proving that even if the Q_w is usually a small fraction of the influent flow, a careful control may have a significant effect on the performance of an activated sludge system.

Eventually, the open loop behavior is also reported; this is a poor policy to adopt, but it is frequently used and is a good reference to understand how the system can be improved by applying controller.

7. DYNAMIC SIMULATIONS

In order to evaluate the performance of the selected control structure, we run the model with time varying data.

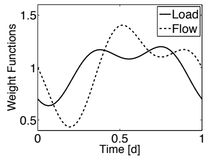

Fig. 2. Typical weight functions for dry weather conditions.

To give a representation of the WWTP behavior, typical variations in dry weather conditions are simulated using the weight functions proposed by Isaacs and Thormberg (1998) and reported in Figure 2. Both inlet flow rate and loads are weighted starting from the nominal conditions in Table 1.

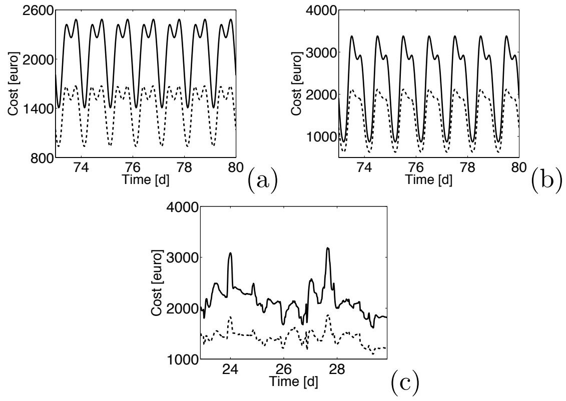

Fig. 3. Dynamic output cost, before (solid) and after the optimization procedure with MLSS controller (dashed).

These data allow to represent the system behavior in different operative situations. Dynamic cost obtained when there is not disturbance in Q_{in} is shown in Figure 3(a) and compared with the costs obtained with the initial values reported in Table 4. A considerably reduction in the operative costs is obtained in this cas. The same holds when the recycle ratio Q_r/Q_{in} is kept constant when the influent flow rate is subject to disturbacens, as reported in Figure 3(b). Especially when high load conditions are encountered, the cost is remarkably reduced.

Eventually, the real plant influent data are used to test the selected control structure. The dynamic cost behavior obtained without MLSS controller (with the initial values in Table 4) and with the proposed configuration including MLSS controller, recycle ratio and DO setpoits constant at their optimal value, is shown in Figure 3(c). Again, the optimized control structure allows a noticeable cost reduction, proving one more time

Configuration		Cost [€/d]			
		Nominal	d_1	d_2	d_3
c_1	Q_r/Q_{in} -SRT	1440	1739	1752	1993
c_2	Q_r/Q_{in} -F/M	1460	1775	1773	2032
c_3	Q_r/Q_{in} -S_{NH}^{eff}	1479	1832	1759	2038
c_4	Q_r/Q_{in} -MLSS	**1446**	**1632**	**1752**	**1869**
(Q_r/Q_{in} Q_w): Open Loop		1466	1777	1783	2046
			d_4	d_5	d_6
c_1	Q_r/Q_{in} - SRT	1440	2390	2442	2779
c_4	Q_r/Q_{in} - MLSS	**1446**	**2056**	**2269**	**2344**
c_8	SRT - $S_{NO}^{p,3}$	1481	2470	2440	2805
c_9	MLSS - $S_{NO}^{p,3}$	1490	2045	2257	2552
(Q_r/Q_{in} Q_w): Open loop		1466	2436	2458	2823

Table 7. Cost investigation for the considered configurations.

that in a WWTP there is the potential for large improvement in operation.

8. CONCLUSION

In this paper, the control design of an ASP in a biological wastewater treatment plant is studied from a process economic point of view. The self-optimizing procedure gives a clear chance to obtain a cost-efficiently controlled process, respecting the effluent requirements as well as the operative conditions. The best configuration Q_r/Q_{in}-MLSS involves the mixed liquor suspended solids controlled by the waste flow and keeping the recycle ratio fixed.

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Dynamic model of a bubbling fluidized bed boiler

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Abstract

A dynamic model for a high-volatile solid fuel fired bubbling fluidized bed boiler is presented. The model consist of a furnace model describing combustion in a bubbling fluidized bed and a model for a water-steam circuit describing heat transfer from hot flue gases to water and steam. The versatile furnace model takes account of quality parameters of fuel so that the effects of moisture, particle size, heat value, and the amount of volatiles can be simulated. The model is based on the first principles mass, energy, and momentum balances. Results from validation of the model against a bubbling fluidized bed boiler process data are presented. The validation of the model showed that the model can describe the dynamics and static gains of the process very well.

Keywords: Dynamic boiler model, bubbling fluidized bed combustion.

1. Introduction

In the modern power generation the dynamic performance of power plants plays a very important role. This is because of the stringent demands of productivity and deregulation of energy markets. E.g. the increasing number of uncontrolled wind turbines connected to the power system disturbs the power balance which must be compensated by other controlled power plants. Also in process industry unit sizes of steam consuming processes, like paper machines have been increased causing bigger load disturbances for industrial power plants.

The most typical way to get information about the dynamic properties of the boiler is to perform test runs to determine e.g. thermal inertia, storage capacity, and load change rate. However, it is quite common that it is not possible to perform all the useful test runs because of the economic, productive, or safety reasons.

The other way to study the dynamic properties of the boilers is simulation. Mathematical modeling of boilers has been interested researchers already for decades [Maffezzoni, 1992]. Some of the pioneering works in this field are the works of Chien [Chien et al, 1958] and Profos [Profos, 1962]. The reported boiler models can be divided into two categories; fairly complicated models and simpler models derived for some limited purposes. The complicated models typically include dozens of nonlinear dynamic equations, static equations, variables and parameters. Some examples of those complicated models can be found e.g. in [Cori and Busi, 1977] and [McDonald and Kwatny, 1970]. In the simpler models many dynamic equations are neglected and many variables are not included. These models are typically applied to control purposes (design and implementation of model based control methods). Examples of this type of models are e.g. [Åström and Bell, 1998, 2000], [Cheres, 1990] and [de Mello, 1991]. Most of these models are focused on the modeling of the water-steam cycle of the boiler, heat transfer from the furnace and the flue gas duct to the water-steam circuit, thermo hydraulics, flow dynamics, etc.

In the boiler models the phenomena in the furnace have been typically left for the minor consideration. The heat power released in the furnace is often handled as a simple first order transfer function from the fuel power demand. With this kind of approach it is not possible to take account the effect of fuel quality parameters to the operation of the boiler. However, especially with biomass fired boilers the quality of fuel may vary remarkably influencing on the performance and usability of the boiler. There is a lot of research work going on about the modeling of combustion of different type of fuels in different type of combustors, e.g. [Scala, 2002] and [Galgano, 2005]. However, the combustion models developed there are seldom connected with the dynamic boiler models. Some reasons for this may be that the combustion models require heavy computing and also it is the different research groups working with combustion models and boiler models and there is a lack of information transfer between these research areas.

The bubbling fluidized bed boiler model presented in this paper is developed in a research project with a boiler manufacturer Metso Power Inc. A moderately complicated combustion model is connected with the water-steam cycle model resulting a dynamic boiler model taking account also physical phenomena existing in the bubbling fluidized bed combustion. The model structure is described and some simulation results and future plans are depicted.

2. Boiler Model

A dynamic model for the high-volatile solid fuel fired bubbling fluidized bed boiler consists of air-flue gas cycle (air preheaters, furnace, and heat exchangers) and water-steam cycle (water preheaters, drum, evaporator, super heaters, and steam attemperation). In addition steam pressure, steam temperature, and feed water control loops are included in the model. The simulator is built with MathWorks Inc's MATLAB/Simulink software. The model is based on the mass, energy, and momentum balances together with constitutional equations.

2.1 Air - Flue Gas Cycle

The furnace is divided into four segments according to the different combustion zones: the bed, the splashing region, the secondary zone, and the freeboard. The structure of the furnace model is shown in fig. 1. The fluidized bed is modeled according to the two-phase theory. In the theory the flow rate through the emulsion phase is equal to the flow rate for the minimum fluidization. Any flow in excess of that required for minimum fluidization appears as bubbles in the separate bubble phase [Toomey and Johnstone, 1952], [Oka, 2004], [Yang, 2003]. The bed is considered isothermal where two phases have uniform temperature. Minimum fluidization velocity is adopted from [Wen and Yu, 1966]. An average bubble size is assumed throughout the bed and calculated according to [Darton *et al.,*1977].

It is assumed that fuel is fed above the bed and it will spread uniformly and immediately across the cross-section of the bed. In the bed section, according to the two-phase theory, combustion takes place in the emulsion phase. Coarse char and fine char particles are burnt there. The coarse char particles can also burst to the secondary zone of the furnace and drop back into the bed. The fine particles can elutriate out from the furnace [Galgano, 2005] and [Scala, 2002]. The elutriation constant for fine char particles is calculated according to [Tasirin and Geldart, 1998].

The rate of combustion is calculated by taking into account diffusive resistance to coarse char particles and kinetic resistance to elutriable size fine particles. Combustion rates depend also on the density and the diameter of the particle and oxygen concentration in the emulsion phase [Borman, 1998]. The fragmentation of fuel particles accelerates the combustion [Raiko, 2005]. The primary fragmentation occurs immediately when the particles arrive at the bed. Attrition and fragmentation by percolation increase the amount of the elutriable size fine char particles. For high volatile biomass, the generation of the fines is proportional to the coarse char combustion rate at the particle surface [Salatino, 1998]. For biomass the average diameter of the fine particles is assumed to be constant, 100 µm [Galgano, 2005]. Devolatilization occurs in the bed section and volatile components burn in the upper zone of the furnace. Devolatilization yields carbon monoxide, carbon dioxide, and hydrogen. The rate of devolatilization is modeled by a simple correlation considering diameter of the fuel particle and temperature of the fluidized bed [de Diego, 2003], [Scala, 2002].

Heat transfer into the walls in the bed section is efficient. The heat transfer coefficient is modeled using the packet-renewal model [Mickey and Fairbanks, 1955], [Basu, 2006]. In the model the packets stay in contact with the wall surface short time and then sweep back to the bed. While the packet is in contact with the wall, the unsteady state heat transfer takes place between the packet and the surface.

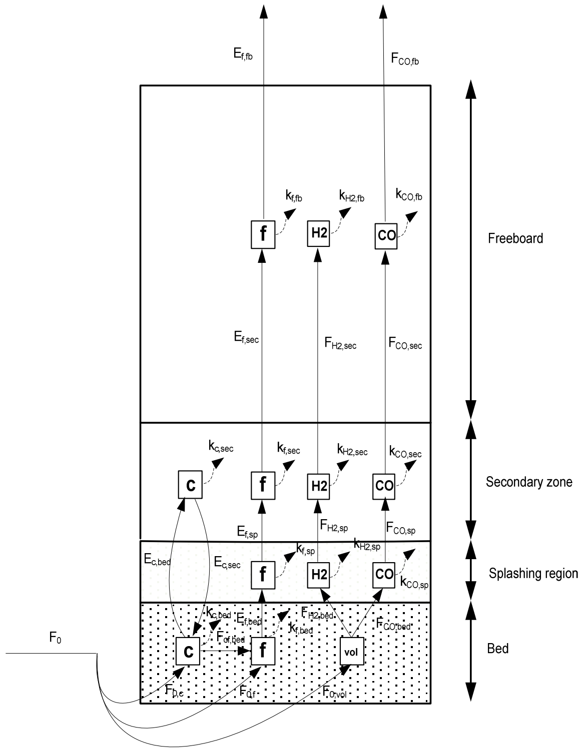

Figure 1. Structure of the furnace model. F_0 = fuel feed, **C** = coarse char balance equations, **f** = fine char particles balance equations, **vol** = volatile matter balance equations, **H2** = hydrogen balance equations, **CO** = carbon monoxide balance equations, E = entrainment of char coal from one zone to another zone, F = mass flow between model zones, k = burning rate of the material.

Inert sand particles are ejected from the surface of the bed into the splashing region. The mass flow is calculated according to [Pemberton and Davidson, 1986]. Gas flows leaving the bubble and emulsion phases are assumed to be instantaneously mixed at a beginning of the splashing region [Okasha, 2007]. A clustering of bed particles is neglected [Benoni, 1994]. The upper edge of the splashing region is assumed to be at the same level with a refractory wall of the furnace and the lower edge depends on the bed height. In the splashing region, all available oxygen reacts with carbon monoxide and hydrogen. Combustion of elutriated fines is assumed to be neglected. Heat transfer is modeled by the packet-renewal model. Secondary air is brought to the secondary zone where the combustion of elutriated fines and volatiles takes place. Tertiary air is brought to the freeboard where some of the elutriated fines and volatiles are burned. Part of the elutriated fines and carbon monoxide can exit the furnace but hydrogen will burn out. In the secondary zone and the freeboard sections heat is transferred to the walls by radiation.

The furnace model is based on the time-depend ordinary differential mass and energy balance equations. The mass balances of fine char particles and oxygen are written in all furnace zones. It is assumed that average velocity of the fine particles equals to gaseous components. In addition in the bed section the mass balances are written for coarse char particles, volatile matter, and bursting sand particles. Energy balances are written for the hot coarse char particles and the bed including sand particles, fine char and gaseous components. It is assumed that the fine char particles are in the same temperature with the bed. The mass balance of the coarse char particles is also defined in the secondary zone. In the splashing region the mass and energy balances of the sand particles are defined. Hydrogen, carbon monoxide, and the water vapor mass balances and fine char and gas energy balances are written for the splashing region, the secondary zone, and the freeboard.

In the heat exchange section of the air – flue gas cycle the heat transfer into the super heaters, feed water preheaters, and air preheaters is calculated. Primary, secondary, and tertiary airs are heated by the air preheaters. In the air preheater model the mass and energy balances of the air and the energy balance of the preheater metal mass are calculated. A schematic diagram of the furnace model is shown in fig. 2.

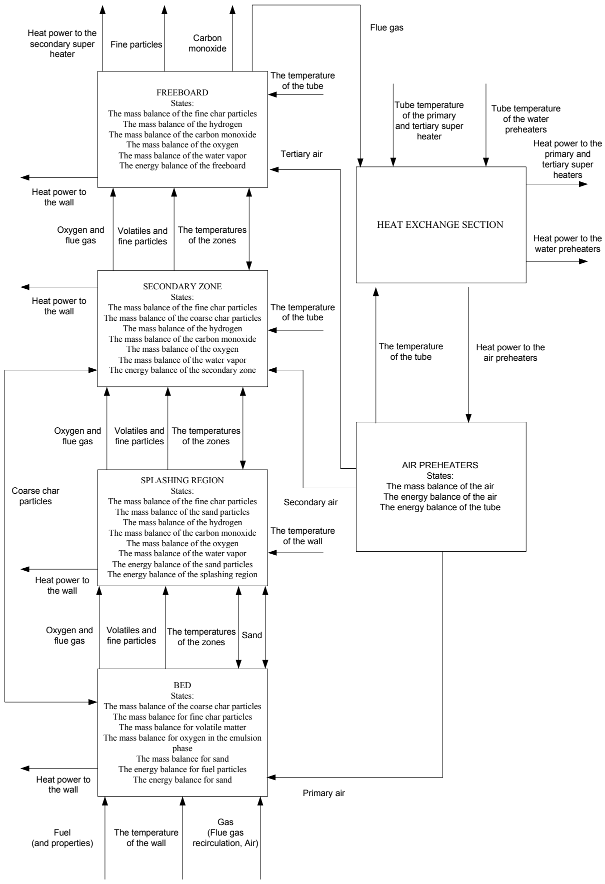

Figure 2. A schematic diagram of the furnace model.

2.2 Water - Steam Cycle

In the evaporation circuit steam is generated inside the vertical tubes located on the furnace walls. Water-steam mixture flows up in a two-phase flow to the drum for phase separation [Adam & Marchetti, 1999].

The evaporation circuit is divided into sixteen segments. Each wall is modeled separately and every wall is divided into four segments according to the furnace segments heights. It is assumed that the water-steam mixture is saturated. The energy balances are written for the water-steam mixture and for the furnace wall tubes. Energy balances for the refractory elements are also written for the two lowest segments of the evaporation circuit. The steam quality and the density of the water-steam mixture are calculated in every segment. Heat flux from the tube wall to the water-steam mixture is calculated by using an experimental equation [Ordys 1994].

Usually the heat flow from the furnace to the evaporator is assumed to be uniform [Åström 2000], [Kim 2005], but in this model the heat flow is divided into each evaporator segment (16 pc.) according to the temperature of the furnace and the heat transfer coefficient in each zone.

Water-steam mixture in the drum is divided into water and steam sub-volumes interacting with each other. The mass balance equation is applied to both sub-volumes and the energy balance is applied to water sub-volume [Kim, 2005], [Ordys, 1994], [Åström, 2000]. From the drum steam is directed to the super heaters. Saturated water in the drum is mixed with feed water coming from the water preheaters. The incoming feed water is directed to the downcomers. In the naturally circulating drum type boilers density difference between the water in the downcomers and the two-phase mixture in the evaporation tubes is the driving force of the natural circulation.

The modeled boiler is equipped with three super heaters and two feed water preheaters. The super heaters are used to raise the live steam temperature. The temperature is controlled by steam attemperating sprays. The feed water preheaters are used to transfer low grade flue gas heat to feed water. The heat exchanger models are based on the mass, energy, and momentum balances. Heat is transferred into exchangers from the heat exchange section of the air-flue gas model. A schematic diagram of the water-steam model is shown in fig. 3.

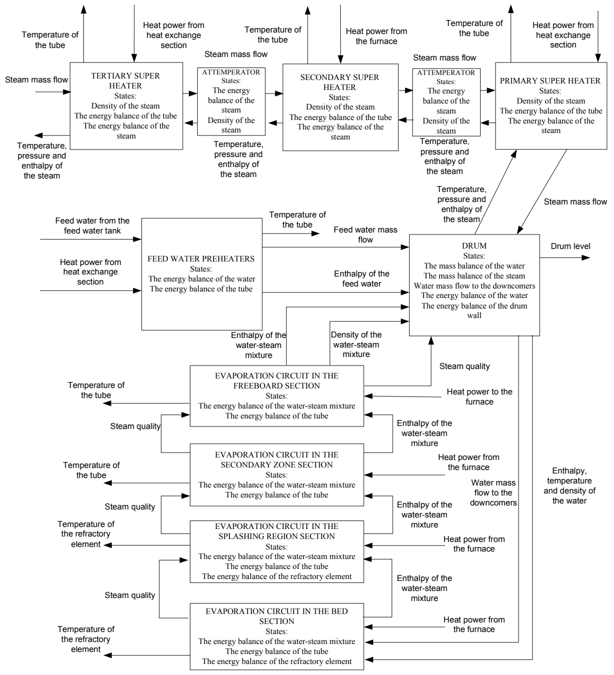

Figure 3. A schematic diagram of the water-steam model.

3. Simulation Results and Future Plans

The model is parameterized using a construction data and measured process data from a 260 MW_{th} bubbling fluidized bed boiler. The validation of the model showed that the model can describe the dynamics and the static gains of the process very well. The model is tested using measured process data as an input to the model and then compared the computed signals with the measured outputs. Figure 4 depicts the measured and simulated results of the drum pressure and the live steam pressure.

The model is used to study the dynamic behavior of the boiler process. The points of interest are e.g. the thermal inertia and the steam storage capacity of the boiler. Knowledge about the behavior of these properties gives useful information for the process and control design. The dynamic model helps process developers to answer questions like how long a boiler can generate steam in case of a boiler trip or what will happen in the process during a black out situation? Figure 5 depicts the boiler dynamic response when the fuel mass flow rate is increased 10 %. From the simulation results e.g. the time delay and the time constant of the boiler can be solved.

In fig. 6 the dynamic behavior of the different zones of the furnace is studied when increasing the moisture content of the fuel 10 %. The control loops are switched on. The temperatures of the bed and the splashing region are dropped slowly due to the thermal capacity of sand.

The future plans of the modeling project are to test the developed model by modeling three different size bubbling bed boilers and compare the simulated results with the measured data. Also the user interface of the simulator will be developed to make the build up of the simulator faster. There is also another project going on with Metso Power to develop a similar simulation model for a circulating fluidized bed boiler.

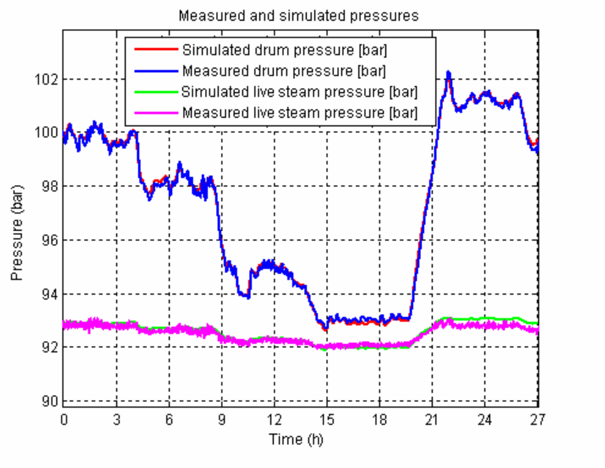

Figure 4. Measured and simulated drum and live steam pressures.

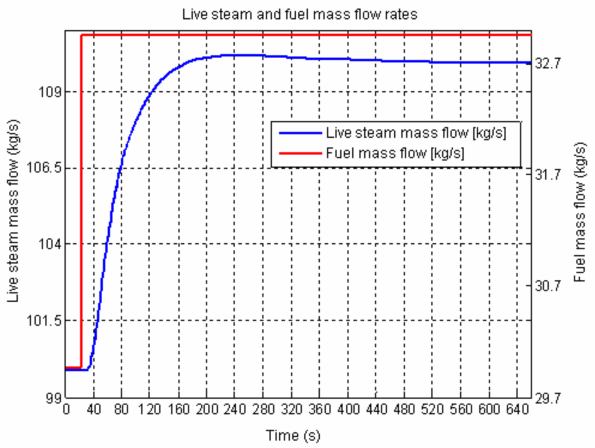

Figure 5. The response of the boiler to the 10 % fuel mass flow rate step change.

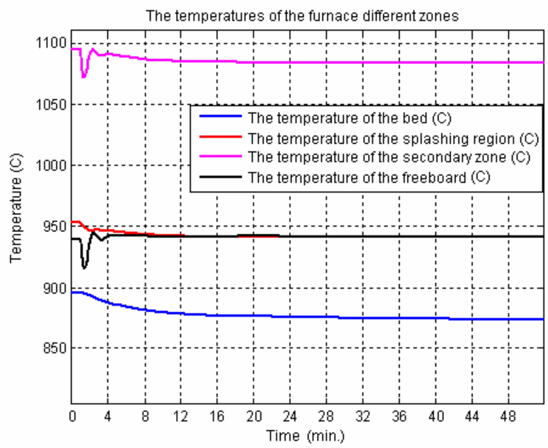

Figure 6. The step responses of the furnace temperatures in different zones when increasing the moisture of the fuel 10%.

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OFFLINE TESTING OF THE FTC-STRATEGY FOR DEAROMASATION PROCESS OF THE NAANTALI REFINERY

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Abstract: In this paper, a scheme for using process monitoring information in process control is presented. The behaviour of an industrial dearomatisation process operated under model predictive control (MPC) is studied in the presence of faults in an online product quality analyser. Different fault tolerant control (FTC) strategies relying on fault detection information provided by process history based quantitative methods are studied utilising both a dynamic process simulator and the MPC. It is shown, that the inherent accommodation properties and model information in the studied MPC provide means to realise the proposed types of FTC strategies.

Keywords: Fault tolerant control, Dearomatisation process, Model predictive control, Process monitoring, Data-based modelling, Online quality analysers

1. INTRODUCTION

In the highly competitive oil refining industry continuous optimisation of the production processes is a crucial factor in keeping the operation economically viable. Increasing the plant availability by improving the equipment fault detection and by more efficient handling the consequent process disturbances is one way for optimising the production. Statistical, quantitative process monitoring methods are tools for fault detection that have lately received a lot of academic interest. Dynamic versions partial least squares regression (PLS) have been developed for continuous processes by (Ku *et al.* (1995), Chen *et al.* (1998), as well as recursive variants of PLS by Qin (1998) and Li *et al.* (2000). State-space models that capture the dynamic properties of processes can now be created with the recently developed subspace model identification method (SMI) that identifies the system matrices from the process history data. During the last decade a number of different algorithms for SMI have been proposed; canonical variate analysis (Larimore, 1990), N4SID (van Overschee and de Moor, 1994), MOESP (Verhaegen 1994) and, more recently, a PCA based method by Wang and Qin (2002). Nonlinear process behaviour is commonly modelled with artificial neural networks (ANN) e.g. multilayer perceptron network (MLP), which is a commonly accepted and widely used feedforward network. A large number of industrial applications of these data-based monitoring methods with successful results have been reported (e.g. Komulainen *et al.* 2004 and Jämsä-Jounela *et al.* 2003 and Kämpjärvi *et al.*, 2007) and reviewed, e.g. by Isermann and Ballé (1997).

However, in spite of the rapid development of the monitoring methods, only few studies have been published about exploiting the information provided by them in process control. Sourander *et al,* (2006) have shown that the inherent accommodation properties of model predictive control (MPC) can readily be exploited to implement different types of FTC strategies providing the necessary monitoring information is available.

In this paper, a method for utilizing monitoring information in process control is introduced in a form of a combined FDI-FTC scheme for a dearomatisation process. An FTC logic for exploiting different FDI results in real-time evolution of the FTC strategies as a function of incipient fault propagation is also presented. The proposed scheme is tested using an experimental platform consisting of a dynamic process simulator and an adaptive multivariable model predictive controller and the corresponding results are presented and discussed. The paper is organised as follows: Chapter 2 is dedicated to introducing the dearomatisation process. In Chapter 3, the fault detection system is presented. Chapter 4 consists of the description of the proposed FTC scheme and Chapter 5 is dedicated to present and analyse the testing results of the models and the FTC system as a whole. The paper ends with a conclusion in Chapter 6.

2. DEAROMATISATION PROCESS

Dearomatisation processes are widely used in the oil refining industry. These processes are used to remove aromatic compounds in the feedstock by hydrogenation. The process studied in this paper consists of two trickle-bed reactors with packed beds of catalyst, a distillation column, a filling plate stripper, several heat exchangers and separation drums, and other unit operations. The quality of the cooled product is measured online by a flash point and a distillation curve analyser. The MPC quality control relies on the analyser values and thus this study concentrates on detecting the faults in the analysers. The process diagram of the studied Neste Oil Naantali Refinery dearomatisation process is presented in Fig. 1.

3. FAULT DETECTION

The aim of the process monitoring is to detect faults in the bottom product flashpoint and distillation curve analysers. The fault detection part of the system is based on process models identified from the plant data with the following methods; PLS, MLP and subspace identification. Process data used in the modelling has been acquired from the Naantali refinery dearomatisation process during winter 2007. About 75 % of this data was used to train the models and the rest was used for evaluation. The measurement values from process variables are 1-

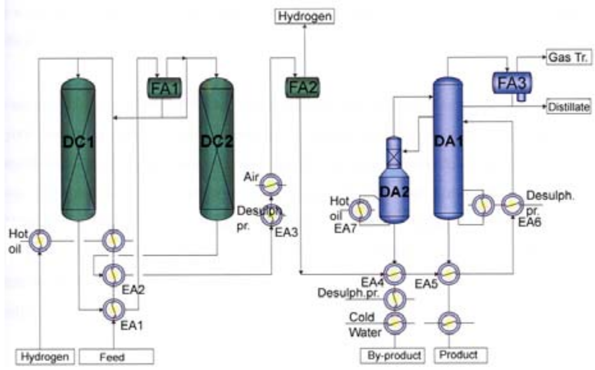

Fig. 1. The Naantali dearomatisation process.

minute averages while the distillation analyser produces assays in about 40 minute cycles and the flashpoint analyser in 3 minute cycles. As the dearomatisation process exhibits substantial transport delays and slow dynamical behaviour, it is necessary to take the process delays into account. The delays have been studied with correlation analysis and the measurements in training data have been time shifted to compensate for the delays.

3.1 Dearomatisation process models

The input variable set (IVS) for the IBP model consists of 6 variables. The input variables and the corresponding delays are presented in Table 1. Five major latent variables were used in the model. The FP model was created with 5 variables in IVS reduced to 3 latent variables. Two variables in the IVS were calculated variables, i.e. variables whose values are not measured directly, but are derived using the measured quantities. Delays for these variables are undetermined, as they are formed using the delay compensated, time shifted measured quantities.

Like most real industrial-sized processes, the dearomatisation process exhibits non-linear behaviour. To improve the modelling capabilities of the linear PLS algorithm, models were augmented with non-linear components, namely MLPs. First, normal PLS models were created and then a residual signal between the measured and estimated analyser outputs was calculated. The residual signal was then modified by bounding it between values -2 and 2. This modification was performed to remove the occasional large absolute values and make the signal better describe the systematic errors in the PLS model. Next, an MLP model was trained with the same inputs as the PLS models, but instead of using the analyser measurements, the residual signal was used as the target output. The final output of the combined PLS-MLP model is the sum of the two separate outputs. The PLS models are the same as described above and the MLP models use the same input variable sets. In the IBP case the MLP has 5 neurons in the hidden layer and in the FP case it has 4 neurons.

Table 1. Variables and corresponding delays of the PLS and state-space models.

Variable	Delays for PLS models (min)		Delays for state-space models (min)	
	IBP	FP	IBP	FP
Column 1 tray 39 pressure compensated temperature [°C]	-66	NU*	-66	-53
Column 1 tray 39 temperature, [°C]	-71	-60	NU	NU
Column 1 reboiling temperature, [°C]	-79	NU	-79	NU
Colunm 1 tray 22 temperature, [°C]	-75	NU	-75	NU
Colunm 1 tray 14 temperature, [°C]	-61	NU	NU	NU
Column 1 top pressure [kPa]	-40	-39	-40	-39
Colunm 2 top pressure, [kPa]	NU	NU	-41	NU
Side product flow, [t/h]	NU	NU	NU	-53
Column 1 reboiler hot oil flow [t/h]	NU	NU	NU	-44
Feed type switch	NU	-206	NU	NU
Column 1 tray 39 - tray 22 temperature, [°C]	NU	U**	NU	U
Colunm 1 tray 14 - tray 6 temperature, [°C]	NU	U	NU	NU
Colunm 1 tray 41 - tray 39 temperature, [°C]	NU	NU	NU	U

* NU stands for 'Variable not used in the model'
** U stands for 'Undetermined'

The state-space models have been identified with a simplified subspace method (Hyötyniemi, 2000) that uses PCA to reduce the dimension of the input variable set. Both models have two states and the IBP model an IVS of five process variables and FP model of six variables, two of which are calculated variables. In addition, the FP model has been augmented with an MLP model that has 3 neurons in the hidden layer. The input variables and corresponding delays of the state-space and MLP models are presented in Table 1.

3.2 Fault detection information

To provide all the necessary information for the FTC, the fault detection system is required to produce other information besides the estimated output values. These additional pieces of information are: reliability of the estimate (RELE), fault indicator (FAULT), reliability of fault indicator (RELF) and estimated magnitude of the fault (FAULTE).

The reliabilities of the estimates of the PLS models are based on the Hotelling T^2 and SPE indices. First the Hotelling T^2 and SPE indices are divided with 10 and 0.004 respectively. These values have been set by analyzing the typical values of the indices with data representing both normal and abnormal situations. After the simple scaling, the values are modified further by using a sigmoid function:

$$y = \frac{1}{1 - e^{-a(x-b)}} \qquad (1)$$

where y is the scaled value, x the original value and a and b are tuning parameters. For the Hotelling T^2, suitable values have been identified to be 0.75 and 10 and for SPE 0.2 and 30. The final value for the reliability is determined by equation 2

$$RELE = 1 - (relHT^2 + relSPE)/2 \qquad (2)$$

where RELE is the final estimate reliability value and $relHT^2$ and relSPE are the scaled Hotelling T^2 and SPE index values.

Fault detection is based on comparing the estimated and real analyser outputs. The residual signal is analysed with a modified version of the Page-Hinckley algorithm. The equations for detecting a positive deviation is given in equations 3-5

$$U_0 = 0 \qquad (3)$$

$$U_n = \sum_{k=1}^{n} (y_k - \mu_0 - \frac{\nu}{2}) \qquad (4)$$

$$m_n = \min_{0 \le k \le n}(U_k) \qquad (5)$$

Where U is the cumulative error sum, y_k the analysed signal, n is the total number of sample in the signal, μ_0 the mean of y, $\nu/2$ is the minimum size of a fault that is possible to detect with this algorithm, m is the minimum cumulative sum over the analysed period and k a time index. A fault in the analysed signal is detected when

$$U_n - m_n \ge \lambda \qquad (6)$$

where λ is the threshold for fault detection. The two modifications to the algorithm are (1) keeping the *max* and *min* values at zero to prevent them from having very large absolute values which could cause problems with computers and (2) clear the cumulative sums after 3 consecutive good estimations to make the fault status return to the normal state faster.

The reliability of a fault is determined based on the ratio of cumulative sums and the threshold limits according to the equation 7. If the reliability of the fault is greater than 1, it is set to 1.

$$RELF = (U/\lambda - 1)/4 \qquad (7)$$

The estimated magnitude of a fault is the residual between the estimated and the true value of the analyser outputs.

4. FAULT TOLERANT CONTROL SCHEME

The proposed FTC scheme (Järvinen *et al.*, 2006) consists of two types of strategies: proactive and reactive.

4.1 Proactive FTC Strategies

Proactive FTC strategies are associated with low fault detection reliabilities. These FTC strategies aim to minimise the effects of potential faults while causing minimal deterioration of control performance if the fault detection turns out to be false. MPC retuning is brought into use when the reliability of fault detection is moderate. The appropriate MPC parameters are automatically retuned to rely less on the measurement as the reliability index of the fault increases. For example, for the distillation analyser a simple feedback filter factor was retuned while for the flashpoint the deadband was used instead. The lower the filter factor, the lower the significance of the new measurement in the control action. For the deadband it is vice versa: the higher a deadband, the lower the significance of the new measurement. Retuning is automatically cancelled if the fault detection turns out to be false.

4.2 Reactive FTC Strategies

Reactive FTC strategies are triggered when the reliability index of fault detection is high. With incipient faults, the reliability of fault detection increases by time due to the progressing fault, and, after some delay, reaches the limit for triggering reactive strategies. The reactive FTC strategies are powerful in cancelling the deteriorating effects the faults have had on control before the fault is detected.

MPC feedback deactivation. Temporary feedback deactivation is performed to prevent the faulty measurement from affecting control. Once the MPC feedback is deactivated, the controller relies on its internal models disregarding the faulty feedback. The controlled variable (CV) predictions do not utilise new measurement information after this deactivation.

Target manipulation. The CV target value is modified by the estimated size of a detected fault to cancel the effects of the faulty feedback on control. MPC feedback deactivation is a necessary prerequisite for using this strategy. This strategy is performed only if fault direction may cause offspec-production.

4.3 FTC Logic

The introduced FTC logic was designed to automatically trigger proactive and reactive FTC strategies based on the fault indicator as well as on the reliability index of fault detection (RELF) ranging from zero to one. FTC is not triggered if RELF is low or if the absolute value of the fault magnitude is adequately high for the MPC to detect the fault by itself. Proactive or reactive FTC strategies are triggered only if there is a fault declared with high enough reliability. Proactive retuning is done with moderate reliability indices. Although the retuning can be a continuous function of the reliability index, in this application three threshold levels; I, II and III, with III being the most severe, were used for easier interpretability of the alarms. MPC feedback deactivation is triggered if the reliability index of fault detection is high. Target manipulation is performed only if the fault magnitude is negative, since only faults with negative fault magnitudes lead to distillation column temperature dropping too low, bringing about a risk of off-spec production. The FTC logic chart is checked once a minute and depending on the value of RELF, retuning actions are automatically activated or deactivated, unless reactive FTC strategies have been triggered, in which case no retunings are active and cannot be activated for the same variable before the fault has been removed. The FTC logic is presented in Fig. 2.

5. TESTING OF THE FTC SYSTEM

5.1 Evaluation of the models' performances

As the FTC system relies on the information provided by the models, the first phase in the testing was to evaluate the models' performances with a completely new data set. The real IBP temperature and the corresponding estimated values for the evaluation period are shown in Fig 3. It can be seen, that all models perform well and that the differences between them are quite small. When the cumulative distribution of estimation errors are analysed (see Fig 4), it can be noted that, on the average, the combined PLS-MLP model produces estimates with smaller error than the other methods as about 90 % of the PLS-MLP estimations deviate less than 3 °C from the correct temperature. After the models' estimation capabilities were tested and found to be acceptable, the FTC strategies were tested offline using a real-time testing system designed to simulate the dearomatisation process

5.2 FTC-system test results

The FTC system was tested on an offline test platform consisting of several proprietary software products all of which run on an MS Windows PC. The most important part of the test platform is the Neste Jacobs NAPCON MPC that is used to control the simulated process in a similar way it controls the real process. The MPC manipulates the set points of the simulator PID controllers for the desired response. The control strategy controls the initial boiling point or the flashpoint of the final solvents. The FTC strategies affect the simulated process in the offline tests by manipulating the MPC.

The dearomatisation process was simulated using the described real-time testing system. A large number of tests were performed during 6 months. In this paper, two typical distillation analyser fault scenario examples are studied: an upward incipient fault and a downward abrupt fault in the analyser result. Throughout these dynamic simulations the MPC was controlling the initial boiling point of the solvent product and the model providing the fault detection information was the PLS model.

A fault progressing at a rate of 1.8 *°C/h* was simulated using the fault generating element included in the PROSimulator model. Proactive and reactive

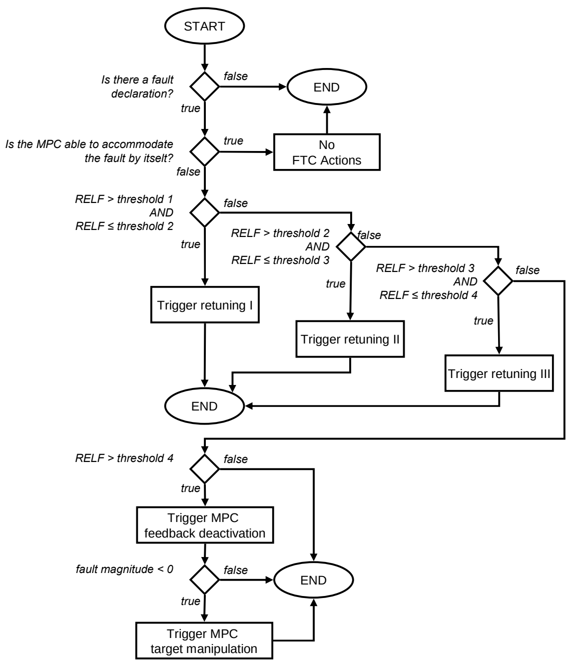

Fig. 2. FTC logic main functions.

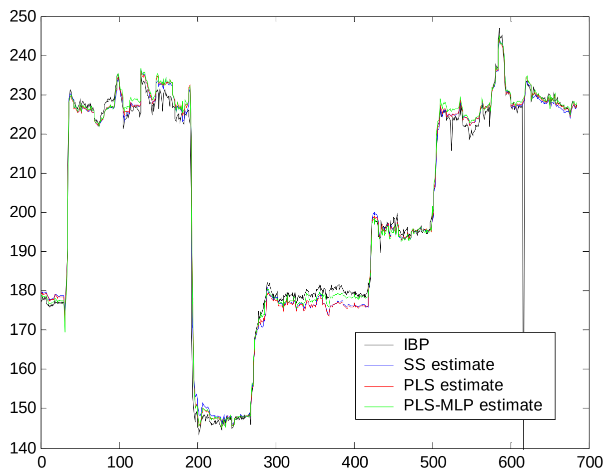

Fig. 3. True IBP temperature and the model estimations with evaluation data set.

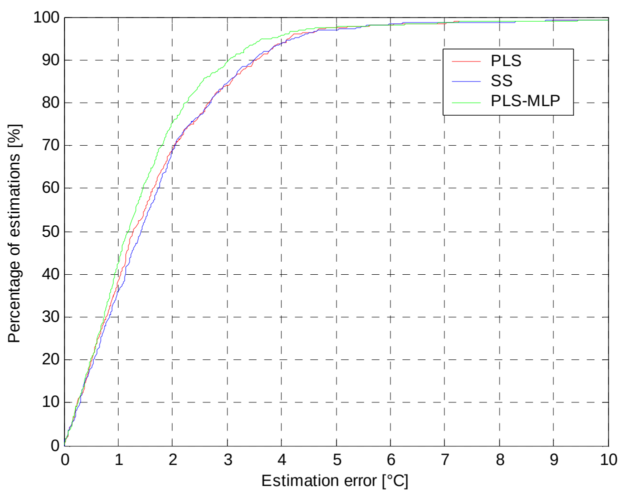

Fig. 4. Cumulative distribution of estimation errors of PLS, SS and PLS-MLP models in IBP temperature estimation with evaluation data set.

FTC strategies were triggered as the FDI system detected the progressing incipient fault. MPC retuning III was triggered first. Upon a new analyser result, the fault detection reliability index increased to a value large enough to trigger the MPC feedback deactivation. Simultaneously the MPC target manipulation was also triggered since the fault was upwards. During the simulation, the FTC strategies were triggered as expected by the software and as a result, the real IBP did not drop significantly as would have happened without the FTC. The target shift was adequate to cancel the effects of the erroneous measurement caused before its detection. The progresses of all relevant variables of this test case are illustrated in Fig. 5.

In the second example, an abrupt downward fault of 4 °C was introduced to the simulation results. A fault of this size was too small for the MPC to detect, but it was correctly detected by the fault detection system and in response to the information produced by the FDI, FTC strategies were triggered. After the fault was detected, the proactive retuning I was triggered by the increasing RELF. When the RELF reached the threshold value, the analyser feedback of MPC was deactivated. Also in this example, the FTC strategies were triggered correctly by the software. In this scenario there was no risk of offspec-production and the target was not shifted keeping the process in a safe condition. The progresses of all relevant variables of this test case are illustrated in Fig. 6.

6. CONCLUSION

An FTC strategy has been developed for Naantali oil refinery dearomatisation process. As a preliminary step before the strategy is tested onsite, the software implementing the fault detection system and the FTC strategies was tested offline in a real-time testing

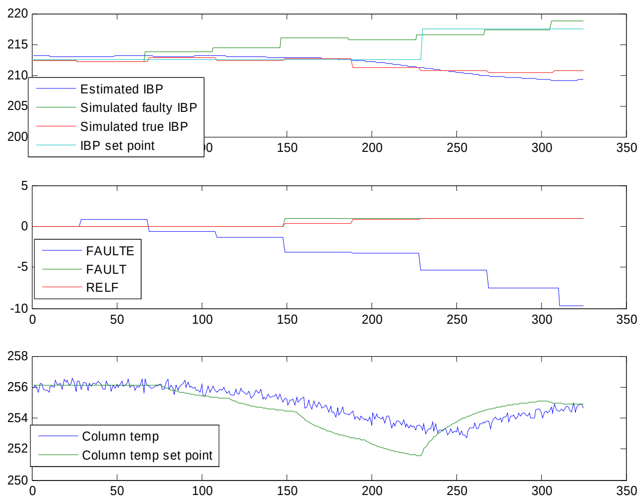

Fig. 5. An incipient fault example in the analyser result. IBP temperatures (on top), FDI information (on middle) and the pressure compensated temperature in column with corresponding MPC set point value (on bottom)

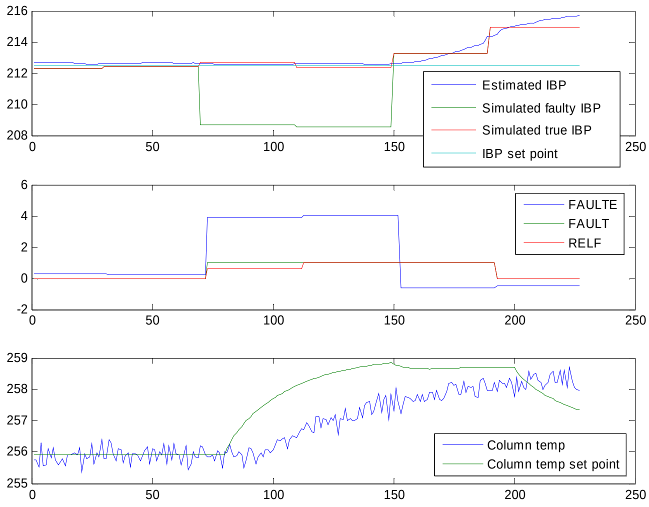

Fig. 6. An abrupt fault example in the analyser result. IBP temperatures (on top), FDI information (on middle) and the pressure compensated temperature in column with corresponding MPC set point value (on bottom)

system specifically designed for these tasks. During the simulations the FTC strategies were triggered in accordance with fault detection information inferred by the FDI. The FDI functions and FTC actions were found to conform to the functional specifications of the system and the simulated process responded as expected. The impact of the FTC strategies via the MPC to the process was as desired. The software was also found to adhere to the strict quality requirements of the refinery. Also, functionality of the FTC logic was correct. Finally, it was concluded that the results of the offline tests were such that proceeding to online refinery tests was possible.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the personnel at the Naantali refinery for their support. This research has been carried out in connection with the EU research project: NeCST – Networked Control Systems Tolerant to faults (IST-004303). The project is partially funded by the European Union. The support is gratefully acknowledged.

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A SOM-BASED APPROACH FOR ANALYSING AND MODELLING A WAVE SOLDERING PROCESS

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Abstract

This paper presents an overview of a data analysis method based on self-organizing maps (SOM), a well-known unsupervised neural network learning algorithm, which was applied to a lead-free wave soldering process. The data analysis procedure went as follows. At first, the process data were modelled using the SOM algorithm. Next, the neuron reference vectors of the formed map were clustered to reveal the desired dominating elements of each territory of the map. At the final stage, the clusters were utilised as sub-models to indicate variable dependencies in these sub-models.

Keywords: Neural Networks, Self-Organizing Maps, Wave Soldering, Process Analysis, Process Modelling.

1 Introduction

Today, new environmental regulations are forcing the electronics industry to reduce and even cease the usage of hazardous products, such as lead-bearing materials and substances containing volatile organic compounds (VOC). Thereupon, the implementation of the lead-free and low VOC processes sets new requirements for process optimisation also in the case of wave soldering, because the earlier process conditions determined for lead containing manufacturing materials may not be applicable to the lead-free process as such. Hence, it can be considered an advantage if the manufacturing processes in the electronics industry can be optimised by data-driven modelling because that way the amount of testing and other experimental activities can be reduced. Additionally, a good computational model helps in reducing the costs of learning through trial and error, which makes the manufacturing process more efficient.

The benefits of the neural network modelling method, or an artificial neural network, ANN, are its flexible modelling abilities and its ability to reveal nonlinear and complex dependencies. For instance, it has been proposed that adaptive neural network methods are more efficient than traditional ones when the functional relations between data elements are nonlinear [1]. Moreover, many studies have indicated already that ANNs can be useful and efficient methods for modelling biological and industrial data [1-6]. However, the applications have been so far principally in the field of dynamical processes, such as energy producing, whereas there have been quite few neural network applications in the field of electronics industry. Thus, studying the suitability of ANN-methods to more discrete manufacturing processes, such as wave soldering, requires some further attention.

In this study, the aim was to determine whether the neural network modelling method could be a useful and time-saving way to analyse a batch-like industrial process, where materials and process substances are combined to make separate and individual, but still similar, products. The wave soldering process, which is one of the techniques used to solder components on printed circuit boards, is ideal for this kind of study, because the process has quite many adjustable factors that can easily have an effect on product quality or, more accurately, on the occurrence of some solder and other defect types.

2 Wave soldering process and data

Wave soldering is one of the electronics manufacturing techniques used to solder components on printed circuit boards. In wave soldering, components and lead wires are attached to a printed circuit board (PCB) as it is transported over a wave of molten solder. The wave solder process consists of three main stages, namely fluxing, pre-heating and soldering. The process is shown in Fig. 1.

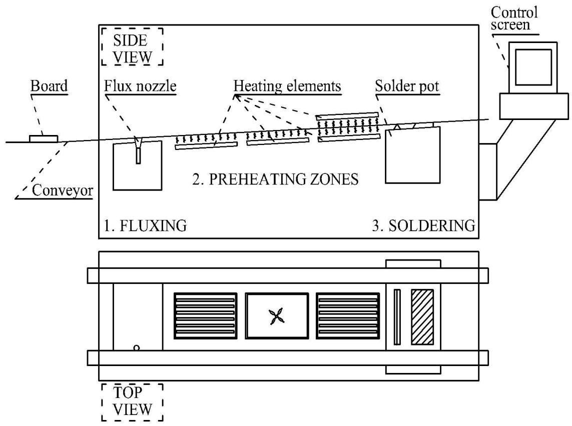

Fig. 1 The wave soldering process

The acquired process data consisted of process information gathered from some test measurements, in which PCBs were put through the wave soldering process using a lead-free solder, more precisely an SAC (Sn-Ag-Cu) solder. In the case of the modelling data, only water or low VOC -based fluxes were used in the fluxing phase of the soldering process. The size of the data matrix used was 418x40 (418 rows, 40 variables in columns). The data consisted of various process parameters and solder defect numbers.

3 Modelling methods

3.1 The SOM

Kohonen's self-organizing map [1] is a well-known unsupervised learning algorithm, and its common purpose is to facilitate data analysis by mapping n-dimensional input vectors to the neurons for example in a two-dimensional lattice. In this lattice, the input vectors with common features result in the same or neighbouring neurons. This preserves the topological order of the original input data. The map reflects variations in the statistics of the data sets and selects common features, which approximate to the distribution of the data points. Each neuron is associated with an n-dimensional reference vector, which provides a link between the output and input spaces and thus describes the common properties of the neuron. This lattice type of array of neurons, which is called the map, can be illustrated as a rectangular, hexagonal, or even irregular organization.

In this case, the raw data were coded into inputs for the self-organizing map. All input values were variance scaled. The SOM having 225 neurons in a 15x15 hexagonal arrangement was constructed. The linear initialization and batch training algorithms were used in the training of the map. A Gaussian function was used as the neighbourhood function. The map was taught with 10 epochs and the initial neighbourhood had the value of 6. The SOM Toolbox [7] was used in the analysis under a Matlab-software platform (Mathworks, Natick, MA, USA).

3.2 Clustering

The K-means algorithm was applied to the clustering of the trained map or, more precisely, to the clustering of the reference vectors. The K-means method is a well-known non-hierarchical cluster algorithm [8]. The basic version of the K-means is started by randomly selecting K cluster centres, assigning each data point to the cluster whose mean value is closest in the Euclidean-distances-sense. Then, the mean vectors of the points assigned to each cluster are computed and used as new centres in an iterative approach.

By clustering the map the interactions can be detected more easily, and the clusters can then be treated as sub-models of the main model, which was formed by the SOM-algorithm. After training and clustering, the desired reference vector elements of clustered neurons were visualised in a two-dimensional space to reveal the possible interactions between data variables.

4 Results and discussion

The map was obtained by training a self-organizing network using the soldering data as inputs. The map is shown in Fig. 2. The SOM map was then clustered according to the ten known flux types by using the K-means algorithm. These clusters are also illustrated in Fig. 2.

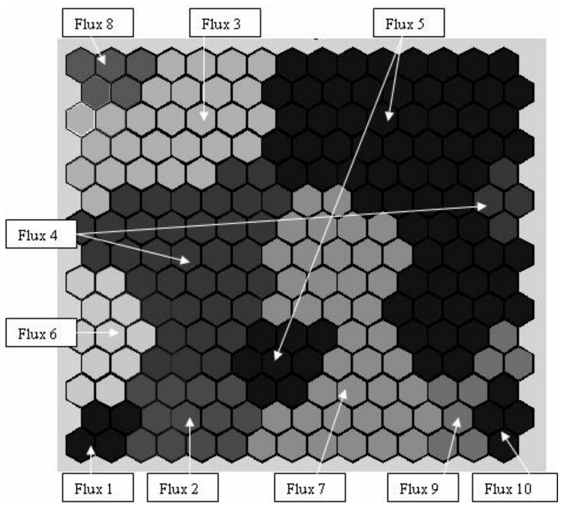

Fig. 2 SOM using the data of a soldering process

As a result of the flux-specific inspection, interesting multidimensional correlations between certain process variables were found after clustering the modelled wave soldering process data. An example on these correlations is illustrated here. In Fig. 3, the neurons of the trained SOM map are presented according to the selected variable components of their reference vectors. The number of balled solders is presented as a function of the solder wave. In the case of flux 3, the appearance of balled solders decreases with the growth of the solder wave intensity. In contrast, in the case of flux 2 the number of balled solders on the PCB increases linearly with the solder wave.

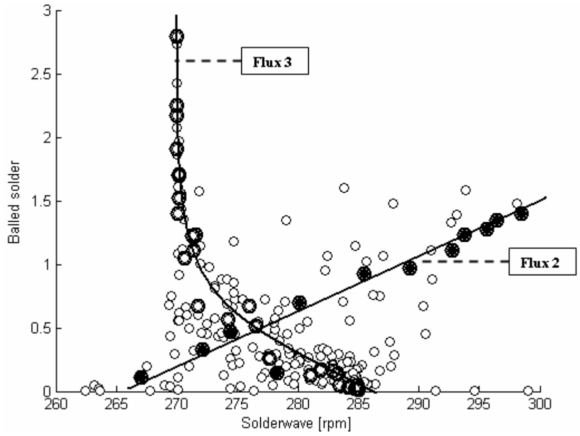

Fig. 3 The number of balled solders presented as a function of the solder wave [rpm] by using the reference vectors of neurons.

As can be easily noticed by examining the Fig. 3, the overall data point pattern in this figure seems rather confusing. It is not possible to detect any clear interaction between the solder wave intensity and the defect number without knowing the flux clusters that are also presented in this figure. On the whole, the reference vector values seem to be located haphazardly in the illustrated two-dimensional space. In contrast, after illustrating the flux clusters as sub-models, the interactions between solder wave and soldering quality are revealed. This leads to the fact that, in this case, creating and studying sub-models is the best way to reveal the interactions.

The implementation of the lead-free processes sets requirements also for the optimisation of the wave soldering process, because the earlier process conditions determined for lead containing manufacturing materials may not be applicable or at least optimal anymore. Hence, the correct adjustment of the wave solder process is important to produce soldered PCBs with high quality and to minimise ineffective process tuning. In this respect, the successful computerised modelling of the process has several advantages including the reduction of the process costs; a more efficient process and a reduced material loss are achieved as learning through trial and error is reduced. Thus, the results of this study seem very encouraging.

5 Conclusion

The results presented in this paper show that the applied SOM-based neural network method is an efficient and fruitful way to model data acquired from the electronics industry. However, further research is still needed to validate the method more widely in the field of electronics production processes. In addition to wave soldering, manufacturing electronics includes other important processes, such as paste printing, component placement, testing, and also other soldering methods. In analysing the wave soldering process, though, the findings seem this far very encouraging considering the successful use of the analysis method developed.

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AN EMBEDDED FAULT DETECTION, ISOLATION AND ACCOMMODATION SYSTEM IN A MODEL PREDICTIVE CONTROLLER FOR AN INDUSTRIAL BENCHMARK PROCESS

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Abstract: The fault detection and isolation (FDI) in industrial processes has been under an active study during the last decade, but fault tolerant control applications that rely on traditional FDI methods have not been widely implemented in industrial environment so far. The most widely implemented FDI methods have traditionally based on model-based approaches. In the modern process industries, however, there is a demand for methods based on the process history data due to the complexity and limited availability of the mechanistic models. In this paper a fault tolerant model predictive controller (MPC) with an embedded FDI system is presented for controlling a simulated crude oil fractionator process, Shell Control Problem (SCP). Three FDI algorithms are applied for achieving the fault tolerance in co-operation with MPC: system based on Principal Component Analysis (PCA), Partial Least Squares (PLS) and Subspace Model Identification (SMI). In addition of the FDI part, fault accommodation part with measurement reconstruction and reference trajectory tracking is implemented. The effectiveness of systems is tested with bias and drift faults in the simulated process measurements. Finally, the results are presented and discussed.
Keywords: FTC, FDI, PCA, PLS, SMI, MPC, shell control problem.

1. INTRODUCTION

During the past decade, fault detection and isolation (FDI) as well as model predictive control (MPC) have been some of the most researched areas in the control field, especially within the process industries. Such popularity has mainly been driven by the demand for developing more efficient and more reliable control systems tolerant to faults. Such demand has been driven by the need of improving the quality of the end products, increasing profits and to meet the tightened safety and economical regulations for complex industrial processes.

Fault diagnosis is generally considered to be one of the most important actions in process plant supervision. Fault diagnosis consists of fault detection, isolation and identification components (Frank et. al., 2000) and, when a fault tolerant control component is added, these are considered to be the main functions of a supervisory fault tolerant process (McAvoy et al., 2004). Without a proper fault detection, isolation and accommodation, the process is vulnerable to faults (Frank et. al. 2000), which may easily render the process unprofitable, unstable and even unusable. Therefore fault detection plays a crucial role in the active fault tolerant control: without proper detection of the fault, an active fault tolerant control strategy cannot be activated to accommodate the faults present in the system.

The fault diagnosis methods are generally divided to process history based methods and methods based on mechanistic models (Venkatasubramanian et al., 2003a). Traditionally, the most widely implemented FDI methods have been based on model-based approaches, but in the modern process industries, there is an increase in the demand for data-based methods due to the complexity and limited availability of mechanistic models. Most relevant data-driven methods are currently based on the principal component analysis (PCA) and the partial least squares (PLS) and for instance, Prantatyasto and Qin (2001), Komulainen et al. (2004) and Vermasvuori et al. (2005) have been using the methods in their research for detecting faults in the measurements of petrochemical processes. Additionally, the dynamic behaviour of the process can be captured from process history data by using subspace model identification (SMI) methods. During the last decade a number of approaches have been proposed for the SMI, for instance, the formulation by Hyötyniemi (2001) and PCA-based approach by Wang and Qin (2002).

MPC has firmly established its position in the petrochemical industry, and the use of the MPC has also been increasing in other areas of chemical process industry and outside industrial environment, as stated by McAvoy et al. (2004) in their milestone report. MPC has been under constant development, and the focus in this research area has recently been on fault tolerance and nonlinear MPC formulations. For instance, Venkateswarlu and Rao (2005) have been studying the use of an MPC equipped with a neural network model to control an unstable nonlinear process. Recent reviews on the MPC technology have been presented by Lee and Cooley (1997), Rawlings (2000) and Qin and Badgwell (2003).

Fault Tolerant Control (FTC) attempts to enhance the availability of a plant by using the measurements and knowledge of the plant model to improve performance and fault-tolerance of the control system. Applications of an FDI connected to active FTC strategies have recently been reported by Pranatyasto & Qin (2001), Prakash et al. (2002) and Patwardhan et al. (2006). The increased amount of applications clearly demonstrates that interest in integrating an FDI and the MPC has increased.

In this paper an FTC system with embedded FDI algorithms for the control of the target process in the presence of measurement faults is presented. Three approaches are used for the FDI design: PCA-, PLS- and SMI-based systems. The process controlled by an MPC and the fault compensation is carried out using the measurement reconstruction and reference trajectory tracking methods. The testing and verification of the systems is carried out with a simulated MIMO process with measurement faults and process noise.

This paper is organized as follows: in Chapter 2 the target process and the sensor faults are introduced. Chapter 3 describes the structure of the FTC. Chapter 4 describes the training of the FDI system and description of the MPC. Chapter 5 contains the results and a discussion. Chapter 6 ends the paper with conclusions.

2. DESCRIPTION OF THE SHELL CRUDE OIL FRACTIONATOR

In oil refineries the crude oil distillation units, also known as crude oil fractionators, are used for initially fractionating the crude oil into different product draws by cooling down the heated mixed-phase oil feed. Usually there are several processing units in series to further separate and refine the desired components of the feedstock to final products. This kind of multi-input/multi-output (MIMO) system is particularly susceptible to analyzer and measurement faults, due to quality variance in the feedstock, difficult process conditions and tight quality requirements.

At the Shell Process Control Workshop Prett and Morari (1987) presented the Shell Control Problem: a model of a crude oil fractionator unit along with a given set of control objectives and constraints. The simulation model was provided by the Shell oil company to act as a performance test for the design of new control strategies. The simulated process unit includes distillation column, four heat exchangers (three side reflux units and one condenser at the top), one side stripper, reflux drum, feedstock stream and three product draws. The target process is described in Figure 1.

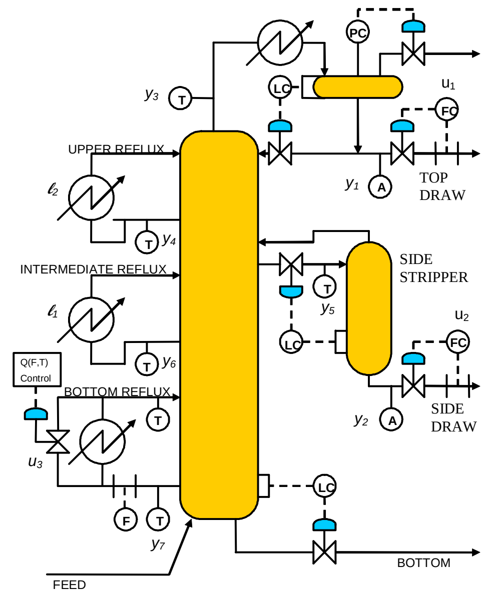

Figure 1. The Shell Control Problem by Prett and Morari (1987).

Hot, mixed-phase oil is fed to the unit and cooled down using reflux flows along the fractionator. The different fractions of the oil are divided to product flows leaving the fractionator. The heat requirement of the system varies, because the reflux streams are reboiled in other parts of the plant.

The bottom heat reflux loop of the fractionator has an enthalpy controller, which regulates the unit heat removal by adjusting the production of the steam on the other side of the reflux. For the purposes of controlling the column, the bottom loop heat duty is used as a manipulated variable (MV). The temperatures of the other two regulating streams are treated as measured disturbances (MD). The distillation end point analyzer measurements, y_1 and y_2, and the bottom reflux temperature y_7 are considered as controlled variables (CV). Finally, for the top and the side draws the product specifications are determined by operating requirements and economics. In addition there is an operating constraint for the temperature of the bottom draw. The gaseous stream in the feed provides all the required heat for the process. Constraints for the input and output variables and the variable rates are given in the following Table 1.

Table 1. The constraints of the Shell Control Problem process (Prett ja Morari, 1987).

Variable	Lower limit	Upper limit
y_1	-0.5	0.5
y_2	-	-
y_7	-0.5	-
u_1, u_2, u_3	-0.5	0.5
$\Delta u_1, \Delta u_2, \Delta u_3$	-0.05	0.05

Since the crude oil fractionator is producing feedstock for the rest of the oil refinery, even small analyzer or measurement errors may lead to large economical losses and accumulation of further disturbances to the other parts of the refinery. It is therefore highly important that the measurement faults in the important fractionator measurements are detected and countered as soon as possible.

3. THE STRUCTURE OF THE FDI/FTC SYSTEM

The FTC system developed in the study is constructed of three parts: the control part for controlling the process, the FDI-system for detecting and measuring the fault magnitude and the supervisory part for carrying out the necessary actions to prevent the effects of the fault.

For detecting and isolating the faults, PCA, PLS and SMI methods are implemented. PCA algorithm is based on the standard formulation by Jackson (1979) and the PLS is constructed using the method by Gerlach et al. (1979) and the NIPALS algorithm developed by Wold (1975). The SMI algorithm used in the study is a simplified version of the SMI formulation, developed by Hyötyniemi (2001). Two different approaches are used for the compensation of the faults: measurement reconstruction (MR), where the faulty signal is compensated with a correction value and a reference trajectory tracking (RTT), where the correction is done by changing the MPC reference trajectory. The alternative fault compensation strategies for the FTC are presented in the Figure 2

4. TRAINING OF THE FAULT DETECTION AND ISOLATION MODELS AND MPC

For the FDI training data is created by simulating the original process model under closed-loop control. Closed-loop data is used, since the MPC would affect the fault detection procedure and thus the effect of the controller should be included within the FDI models. Also, Pranatyasto and Qin (2001), have stated in their study, that it is more favourable to use closed-loop training data for PCA training when designing FTC system for an MPC-controlled process. In general, the training data is selected to be such that it would contain as much variance as possible to capture the characteristic behaviour of the process.

All output and manipulated variables are used in the creation of the FDI models. The output variables are: analyzer outputs y_1 and y_2 and temperature measurements y_3, y_4, y_5, y_6 and y_7. The manipulated variables are the top draw flow u_1, the side draw flow u_2 and bottom reflux flow u_3.

5.1 FDI training

Principal Component Analysis. A PCA model is formed using seven process measurements. In the final model 97 % of the total variance is captured by using two PC's. For FDI purposes, squared prediction error (SPE) and Hotelling T2 limits are calculated with 85 % confidence in both cases. The SPE limit is formed by using the left-out PC's and the method by Jackson (1979). The Hotelling T2 limit is calculated using the standard T2-formulation.

Partial Least Squares. The training data for the PLS uses the same set of data that has been used with the PCA. The PLS latent variables are calculated using the NIPALS algorithm by Wold (1975). In the final model there are four latent variables (LV) which captured about 99 % of input variance and about 75 % of the output variance.

Subspace Model Identification. The training data used for the SMI is same set of data that is used with the PCA. When creating the state-space models, the order of the model is reduced from 35th order model to 10th order model to optimize calculations.

5.2 MPC

The MPC used a 10th order reduced model. Due to this fact, no robustness problems are encountered with the MPC. The MPC parameters are presented in the following Table 2.

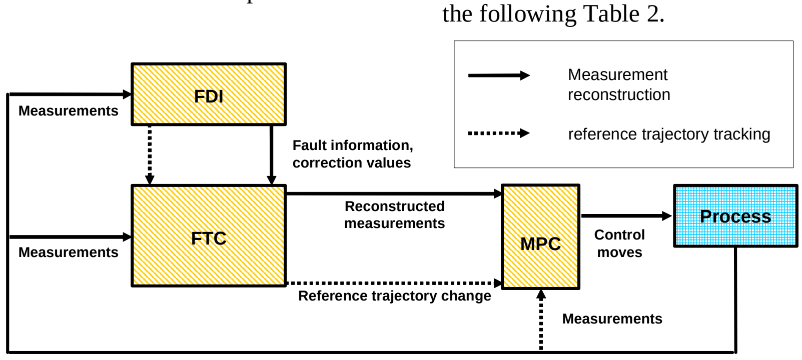

Figure 2. The alternative fault compensation methods for the FTC system.

Table 2. The MPC parameters for controlling the Shell heavy oil fractionator.

Parameter	Values
Prediction horizon p	120
Control horixon m	40
Weights, CV [y_1, y_2, y_7]	[45 45 45]
Weights, MV	[0.01 0.01 0.01]
Weights, MV rates	[1000 1000 1000]

5. TESTING, RESULTS AND DISCUSSION

The evaluation of developed FTC systems is carried out by implementing the Shell Control Problem in Matlab environment. Random noise is added to the measurement signals in order to reflect the situation with the real process measurements. The magnitude of the noise varies between -0.025 to 0.025, which is 5% of the operating range measurement y_1. Bias and drift faults are introduced to the simulated measurements during the simulation. Whole data set consisted of 800 minutes of simulated process data including measurement errors.

5.1 Faults

Two different kinds of faults are common in oil refining process analyzers and sensors: abrupt bias faults and slowly increasing or decreasing drift faults. Bias faults are usually caused by the contamination of the analyzer sample. The drift faults are commonly caused by a slow accumulation of substance into the sensors or analyzers. In this study, these two fault types are introduced to simulated process measurements. Positive bias fault with a magnitude of 0.5 and a positive drift fault with a target value of 0.5 are introduced to the measurement y_1 at time 100 minutes and lasted for 200 minutes after which the fault is removed from the measurements.

5.2 The performance of the FTC systems

First, the FTC system based on PCA tested on the simulated data set. Since the SPE is more sensitive to unexpected disturbances than the Hotelling T2, it is decided that the SPE would solely be used as a fault detection index in this study. Hotelling T2 index is used for reference and verification purposes.

The PCA-based FTC system is immediately able to detect the bias fault in the process measurement y_1 and the fault is quickly compensated for. The fault had almost no effect at all to the performance of the process. The drift is detected later than the bias fault, but is also detected and quickly compensated to prevent further effect to the process. The SPE index and Hotelling T2 index in the case of the bias fault are presented in Figure 3 and for the drift fault in Figure 4.

As it is seen from these figures, the calculated limit in the Hotelling T2 is much higher and thus unable to detect the fault. In both cases the faults are detected at ease with the SPE index.

Two strategies were implemented with the PCA: measurement reconstruction and reference trajectory tracking.

The performance of the PCA-based FTC system with measurement reconstruction (MR) is presented in Figure 5 for the bias and drift faults. The performance of the PCA-based FTC-system with reference trajectory tracking (RTT) is presented in Figure 6 for the bias fault and in for the drift fault.

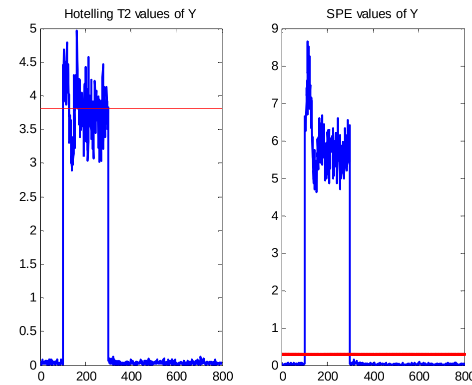

Figure 3. The Hotelling T2 and SPE indices and limits for the bias-shaped fault in the measurement y_1.

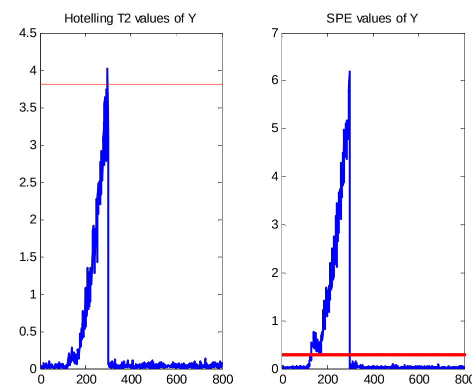

Figure 4. The Hotelling T2 and SPE indices and limits for the bias-shaped fault in the measurement y_1.

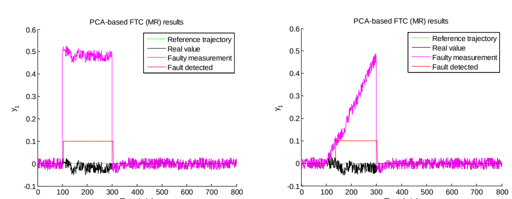

Figure 5. PCA-based FTC (MR) results with bias and drift faults in the process measurement y_1.

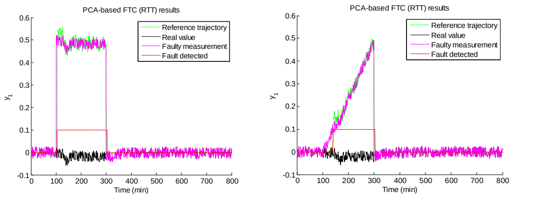

Figure 6. PCA-based FTC (RTT) results with bias and drift faults in the process measurement y_1.

After detecting a fault in the system, a fault isolation procedure based on SPE contribution plots is engaged. As an example, in the case of a bias fault a contribution plot for time step t= 240 is presented in the Figure 7. In the contribution plot, the measurement y_1 is classified as being faulty as can be seen from the figure. The fault identification is carried out by using an iterative procedure based on the SPE score.

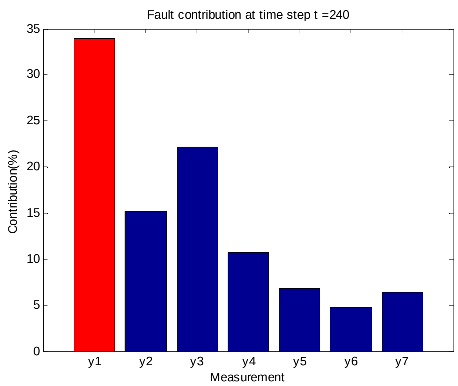

Figure 7. The SPE- contribution plot at time step t=240 when a bias fault in the measurement y_1.

PLS-based FTC-system consists of root mean square of prediction error (RMSEP) index for fault detection and PCA for fault isolation on the output vector. The RMSEP index is then compared with the experimentally determined detection limit and if value is over the limit, fault is declared. Both measurement signal reconstruction and reference trajectory tracking FTC-strategies were used. In general, the RMSEP is able to detect the faults in the measurements as is seen from Figure 8 for the bias and drift faults. The results from using the PLS-based FTC with measurement reconstruction are presented in Figure 9 for bias and drift faults and for reference trajectory tracking in Figure 10 for bias and drift faults.

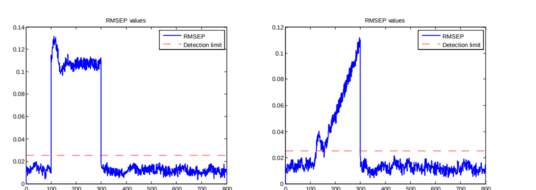

Figure 8. The RMSEP values for the measurements in the case of a bias and drift fault in output y_1.

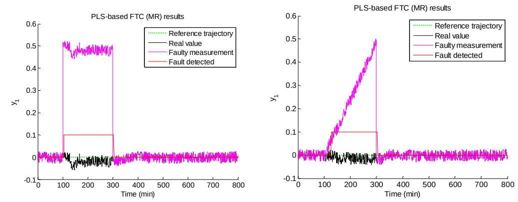

Figure 9. PLS-based FTC (MR) results with bias and drift faults in the process measurement y_1.

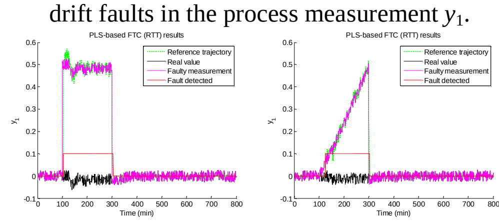

Figure 10. PLS-based FTC (RTT) results with bias and drift faults in the process measurement y_1.

The SMI-based system detects the faults by comparing the model outputs with the measurement outputs and comparing the achieved a residual value with the detection limit at each time step. If the residual value is higher than predefined limit, a fault is declared and isolated to that specific measurement. When a fault is present in one of the measurements, the model output is used instead of measurement value until the fault had ended and the residual returned under the limit. The residual curve can be observed in Figure 11 for bias and drift faults. The results of the SMI-based FTC using measurement reconstruction is presented in Figure 12. The results from the reference trajectory tracking strategy are seen from Figure 13.

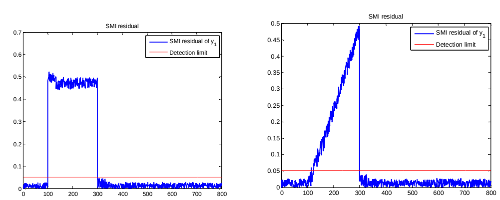

Figure 11. The SMI residual for the measurements in the case of a bias and drift faults in output y_1.

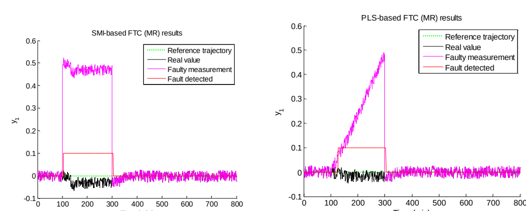

Figure 12. The performance of the SMI-based FTC system with of the bias and drift faults in y_1.

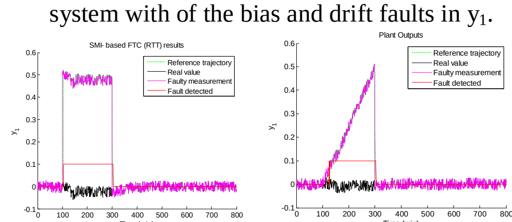

Figure 13. The performance of the SMI-based FTC system with of the bias and drift faults in y_1.

5.3 Analysis of the results and discussion

Based on the results presented in the previous section, the faults introduced to the system are effectively detected, isolated and compensated with the presented FTC systems. The bias faults were detected as soon as they were present in the measurement and drift faults with reasonable delay. Both fault compensation approaches, measurement reconstruction and reference trajectory tracking were working effectively. All presented FTC systems work efficiently and the fault detection and isolation rate is good on all cases.

6. CONCLUSIONS

In this paper, PCA, PLS and SMI methods have been presented for fault detection, isolation and identification purposes to achieve fault tolerance with MPC. FTC systems based on these methods are successfully implemented for controlling a simulated crude oil fractionator unit with faults present in the measurements. Based on the results, the methods proved to be effective and the FTC systems are able to counter the different faults in the simulated process measurements. In the PCA -based system the use of SPE as a fault detection index is a good choice, because the resolution of the method is better than with the traditionally used Hotelling T2, which detects faults much later than SPE in the test setting. With PLS, The RMSEP index based on latent variables provided good results and the detection rate is faster than with the PCA. The SMI also worked effectively and faster than PCA and PLS, although the performance of the SMI was heavily affected by the accuracy of the SMI model.

The fault compensation strategies, measurement reconstruction and reference trajectory tracking, provided similar results, the difference between the two approaches being small. The reference trajectory tracking, however, seems more appropriate that the measurement reconstruction, since it only requires modifications on the controller parameters, not on the measurements themselves. Overall the results clearly indicate that all the presented methods are promising additions to be implemented for real industrial process use. It is worth noting that the data used in the study is simulated; therefore the results are probably better than they would have been if real process data would have been used instead.

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ENHANCED CAUSAL DIGRAPH REASONING FOR FAULT DIAGNOSIS WITH APPLICATION ON THE PAPER MACHINE SHORT CIRCULATION PROCESS

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Abstract: This paper presents a new fault diagnosis method based on the combination between the dynamic causal digraph reasoning method and the Kalman filter. The dynamic causal digraph method is used to locate the fault on the variables, and the Kalman filter is used to further improve the fault diagnosis result by locating the fault on the arcs. An application of the proposed method on the paper machine short circulation process is presented. The results show the proposed method is able to find the responsible arcs in the case of process faults.

Keywords: Causal digraph, Kalman filter, APROS, CUSUM method

1. INTRODUCTION

Research in the field of fault diagnosis has been very active since the 70s. In order to meet the demand from industries concerning quality, efficiency and safety, numerous fault diagnosis methods have been developed, among which causal model based methods have attracted attentions since the first development by Iri et al. (1979). As a modeling method, causal model is able to describe the system behavior in terms of cause-effect relationships between system's entities, which is represented by a directed graph. The causal models can be used for many different purposes such as fault diagnosis (Montmain & Gentil, 2000).

The fault diagnosis method based on causal models was created by integrating causal theory with graph theory. Due to the broad definition of a cause-effect relationship, there have been dozens of fault diagnosis methods developed based on different interpretations of it. Dynamic causal digraph method developed by Montmain & Gentil(2000) uses difference-algebraic equations to describe the cause-effect relationships. This enabled the development of the inverse inference mechanism. This inference mechanism simplifies the fault location step by using consistency tests for the local model and by tracking the fault origin nodes in the MISO structure of the causal model. As reported by Montmain and Gentail (2000), the dynamic causal digraph method is able to manage different types of: sensor, actuator and process fault. . However, the ability of the dynamic causal digraph method to handle process faults is limited, because it is assumed that a primary fault is a change in the variable (node in the digraph) rather than a change in the consistency between variables (arc in the digraph), which is not true for the process fault cases. Moreover, it is usually required to know the corresponding faulty process component in the industrial application, which brings up the topic to locate the fault on the arcs of causal digraph.

To meet the requirement of locating the fault on the arcs, the Kalman filter technique is introduced into the causal digraph to update the parameters of the arcs, because Kalman filter is able to track time-varying model parameters while handling process noise.

The paper is organized as follows. In Chapter 2 the proposed method is described. In Chapter 3 the short circulation process of the paper machine, testing environment and the studied fault scenario are introduced. The fault diagnosis results of the fault scenarios are shown in Chapter 4 followed by the conclusions in Chapter 5.

2. FAULT DIAGNOSIS WITH CAUSAL DIAGRAPH AND KALMAN FILTER

In this chapter a new combined fault diagnosis method integrating the dynamic causal digraph method and the Kalman filter is proposed for the purpose of locating the fault on the arcs. The proposed method performs the fault detection and isolation in four steps as follows:

1. Generate global (GR) and local residuals (LR) with the dynamic causal digraph
2. Detect possible abnormality in the residual signals with the CUSUM method
3. Locate the primary fault and identify the nature of it using the fault isolation and nature rules
4. In the case of a process fault, a Kalman filter is used to update the parameters of the arcs. The changes in the parameters indicate the faulty arcs.

In this case static models are used to describe the cause-effect relationships between variables, since the dynamic causal digraph method is applicable for general linear models.

2.1 Residual Generation with the causal model

Dynamic causal digraph produces two kinds of residuals to be used in fault detection and isolation: global and local residuals. The global residual is produced for the purpose of fault detection by the difference between the measurement and the global propagation value as shown below:

$$GR(Y) = Y(k) - \hat{Y}(k) \qquad (1)$$

where Y(k) is the measurement and is the global propagation value obtained by

$$\hat{Y}(k) = \hat{u}(k)^T \theta(k) \qquad (2)$$

where $\hat{u}(k) = [\hat{u}_1(k),....\hat{u}_n(k)]^T$ is the lagged global propagation value from the predecessor in the digraph model, *n* denotes the number of the inputs for the variable *Y*, and $\theta(k) = [\theta_1(k), \theta_2(k),...., \theta_n(k)]^T$ is the parameter vector of linear regression.

The local residuals are further subcategorized into three types: individual local residuals (ILR), multiple local residuals (MLR) and total local residuals (TLR). The individual local residual is produced by taking the difference between the measurement and the local propagation value with only one measured input while all the others are propagation values from the parent nodes.

$$Y'(k) = u_m^T(k)\theta(k)$$
$$ILR_Y(m) = Y(k) - Y'(k) \qquad (3)$$

where $u_m(k) = [\hat{u}_1(k),..u_m(k),..\hat{u}_n(k)]^T$, $\hat{u}_i(k)$ is the global propagated value from the predecessors, $u_m(k)$ is the measurement for the parent node.

Similarly the $MLR_Y(P)$ is produced with input $u_Q(k) = [\hat{u}_1(k),..u_j(k),..\hat{u}_n(k)]^T$, $j \in Q$, Q is the set of subscript of the predecessors which use measurement as input; the $TLR(Y)$ is produced with $Q = Q_Y$, where Q_Y is the set of subscript of all the predecessors of *Y*.

2.2 Residual Evaluation with the CUSUM method

The CUSUM method is used to evaluate the generated residual signals due to its insensitivity and usability related to the noise and outliers in the measurements.

The residual signals produced are mapped to one of the set {0, 1, −1} by the CUSUM method. In the faultless case, the residuals are assumed to be zero mean random sequence signals, and in the case of fault the mean value of the residual signal will change in two possible directions: positive jump and negative jump.

The CUSUM algorithm (Hinckley, 1971) for positive mean jumps is given by the following equations

$$\sum(k) = \sum(k-1) + \delta(k) - \mu_0 - \beta/2 \qquad (4)$$
$$\sum\nolimits_{\min}(k) = \min\left(\sum\nolimits_{\min}(k-1), \sum(k)\right) \qquad (5)$$

where β is a user specified minimum detectable jump, $\delta(k)$ is the residual signals and μ_0 is the mean value of the nominal signal. Whenever $\sum(k) - \sum_{\min}(k) > \lambda$, a jump has been detected. β and λ are design parameters, usually tuned according to the requirement for false alarm and missed alarm rates. The parameter λ also provides the robustness to the fault detection meanwhile it delays the detection. Similar algorithm for detection of negative mean jump can be easily obtained by modifying Equation 4 and 5. In the rest of the paper, the result of the CUSUM method will be denoted as function CU ( ).

2.3 Fault isolation reasoning with rules

The fault isolation is done by recursively performing local consistency tests using a set of isolation rules on the results of the CUSUM evaluation. These isolation rules, developed by Montmain and Gentil (2000), are converted into a truth table for the convenience of implementation, as shown in Table 1.

The nature of the fault is identified by testing how the fault propagates to its children nodes, after the fault origin is located on the nodes. If the fault propagates through the digraph globally, it is identified as a process fault; otherwise it is defined as a local measurement fault. The rules to identify the nature of the fault are simplified into a truth table, as shown in Table 2.

Table 1. Fault isolation rules of the dynamic causal digraph.

$CU(GR(Y))$	$CU(TLR(Y))$	$CU(ILR_Y(m))$	$CU(ILR_Y(i))$	$CU(MLRY(P_1))$	$CU(MLR_Y(P_2))$	Decision
0	0	0	0	0	0	No fault
1/−1	0	0*	1/−1*	0*	1/−1*	Fault propagates from the parent node *m*
1/−1	0	1/−1**	1/−1**	1/−1**	0**	Fault propagates from the nodes with subscript in P_2
1/−1	1/−1	1/−1	1/−1	1/−1	1/−1	Local fault on variable *Y*

* $\forall i \neq m, i \in P_Y$, $m \in P_1$, $m \notin P_2$, P_Y is the set of subscripts of parents nodes of the node *Y*.

** $\forall i, m, i \in P_Y, m \in P_Y$, $\forall P_1, P_2 \subseteq P_Y$

Table 2. Fault nature rules of the dynamic causal digraph.

$CU(GR(X))$*	$CU(TLR(X))$	Fault nature
1/−1	1/−1	Local fault for that child node
1/−1	0	Process fault for the faulty node
0	1/−1	Measurement fault for the faulty node

*X is the subscript of any child nodes of the node Y.

2.4 Locating the fault on the arcs with Kalman filter

The Kalman filter is used to update the parameter for the arcs after the process fault is identified by the causal digraph method, since the model for the cause-effect relationship is in the form of the static model as given in Equation 2. The random walk model for the parameter estimation is introduced due to lack of knowledge of the dynamics of the parameters, this yields

$$\theta(k) = \theta(k-1) + w(t) \quad (6)$$

$$Y(k) = u^T(k)\theta(k) + e(t) \quad (7)$$

where $w(t)$ and $e(t)$ are uncorrelated zero-mean Gaussian noise with covariance matrix $R_1(t)$ and $R_2(t)$ respectively. The parameter $\theta(k)$ can be estimated using the Kalman filter as (Ljung 1999)

$$\theta(k) = \theta(k-1) + K(k)(Y(k) - u^T(k)\theta(k)) \quad (8)$$

in its recursive form, where the Kalman gain $K(k)$ is given as

$$K(k) = \frac{P(k-1)u(k)}{R_2(k) + u^T(k)P(k-1)u(k)} \quad (9)$$

$$P(k) = P(k-1) + R_1(k) - K(k)u(k)P(k-1) \quad (10)$$

The initial values for the parameters are obtained from the causal models, and the $P(0)$, $R_1(t)$ and $R_2(t)$ are obtained using the recommendations by Ljung (1999).

The obtained time-varying parameters form noisy signal sequences, which are evaluated by using the CUSUM method. Detected parameter changes are assumed to correspond to faulty arcs in the digraph.

3. CASE STUDY

This paper provides three case study concerning fault detection and isolation on the paper machine short circulation process. The studied fault is retention drop on wire section as process fault. For this study, the Advanced Process Simulator (APROS) developed by VTT (Technical Research Centre of Finland) has been used as a testing environment. In the remainder of this section, the short circulation process, the testing environment and a presentation of the fault scenario are described together with the linearity test of the studied process.

3.1 Short circulation process description

The short circulation is a crucial part of the papermaking process, with several important functions. The dilution of the fiber suspension entering the process to a suitable consistency for the headbox takes place in the short circulation, in a mixing process where low-consistency water from the wire pit is mixed with high-consistency stock. The second important task of the short circulation is the removal of impurities and air. This task is performed in the hydro cyclones, machine screens and the so-called deculator. The short circulation also improves the economy of the process because the valuable fibers and filler materials that pass through the wire are recycled. As the intermediate process between stock preparation and former, the short circulation process is also very important for paper quality control, since the most important paper qualities such as basis weight, ash rate and fiber orientation are controlled in the short circulation part. Table 3 lists the most important measurements in the short circulation process and the paper quality measurements.

3.2 Testing environment and fault scenario

The case studies have been carried out in the simulation environment of APROS. The APROS paper machine simulator provides a set of predefined process component models that correspond to the concrete process devices such as pipes, tanks, headbox, drying cylinders and etc., while the solution algorithms are hidden from the users. One built-in paper machine model was provided by the VTT for basic simulation, based on which the control loops were added and the process components were parameterized according to the typical setup of paper making process (Paulapuro, 2000; Karlsson, 2000b; APROS, 2005). The APROS paper machine model with control loop is shown in Figure 1.

One process fault was introduced to the APROS paper machine model, where the basis weight valve blocked partially. In the APROS model, the fault was introduced by increasing the parameter 'nominal pressure drop' of the basis weight valve from 30kPa to 36kPa.This fault is usually caused by the flocculation of fibres, which makes the flow area of the valve smaller than normal.

Table 3. Description of the variables in the short circulation.

Variables	**Description**	**Type**	**Unit**
baval	Basis weight valve opening	Actuator	−
wp_fc	Filler consistency in the wire pit	Measurement	%
wp_fic	Fiber consistency in the wire pit	Measurement	%
fival	Filler adding valve opening	Actuator	−
de_fc	Filler consistency in the deculator	Measurement	%
de_fic	Fiber consistency in the deculator	Measurement	%
hb_fc	Filler consistency in the headbox	Measurement	%
hb_fic	Fiber consistency in the headbox	Measurement	%
feedpump	Headbox feed pump rotation	Actuator	%
totalflow	Mass flow into the headbox	Calculated value	kg/s
bw	Basis weight of paper	Measurement	g/m^2
ash	Ash consistency of paper	Measurement	%

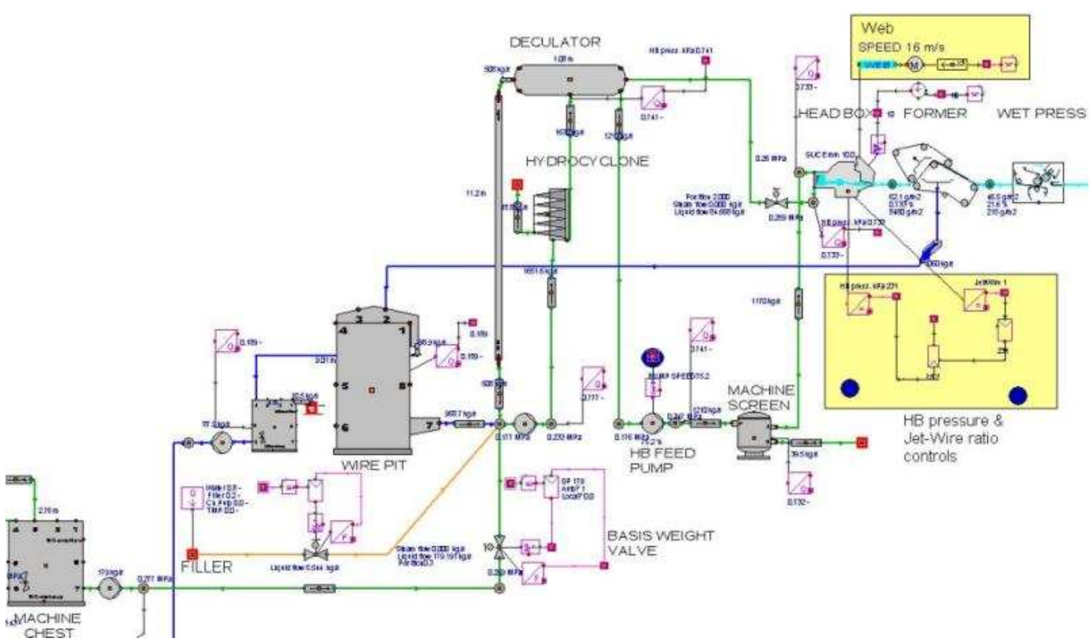

Fig.1. APROS paper machine model

4. RESULTS

The causal digraph model was constructed with the variables listed in Table 3. The structure of the causal model was built according to the causal analysis of the process and the static linear regression models were used to represent the cause-effect relationships as shown in Equation 2. The parameters of the models were identified from least square method. In testing the APROS paper model was run with all the control loops closed and the process fault was introduced into the simulation. The total simulation time was 9800 seconds and the sampling time was 10 seconds. The fault was introduced into the process at time periods 1800-5800s.

With the dynamic causal digraph, a set of residuals were generated and evaluated by the CUSUM method. The fault isolation rules and nature rules were applied to locate the fault origins in the digraph model as shown in Figure 2.

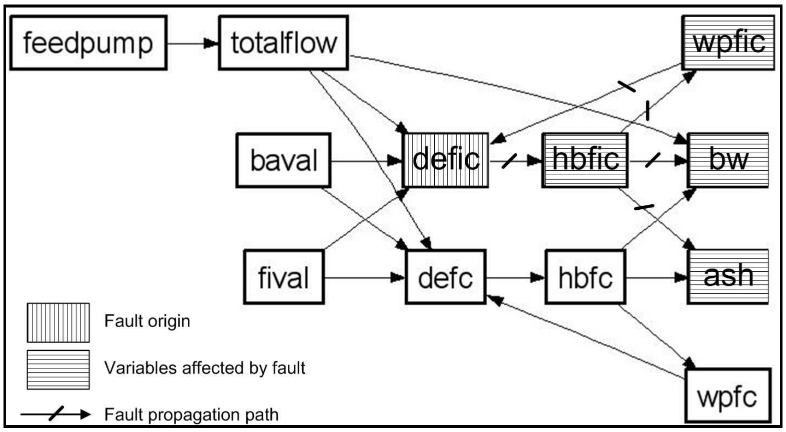

Fig.2. Fault diagnosis results with causal digraph method (1800-5800s)

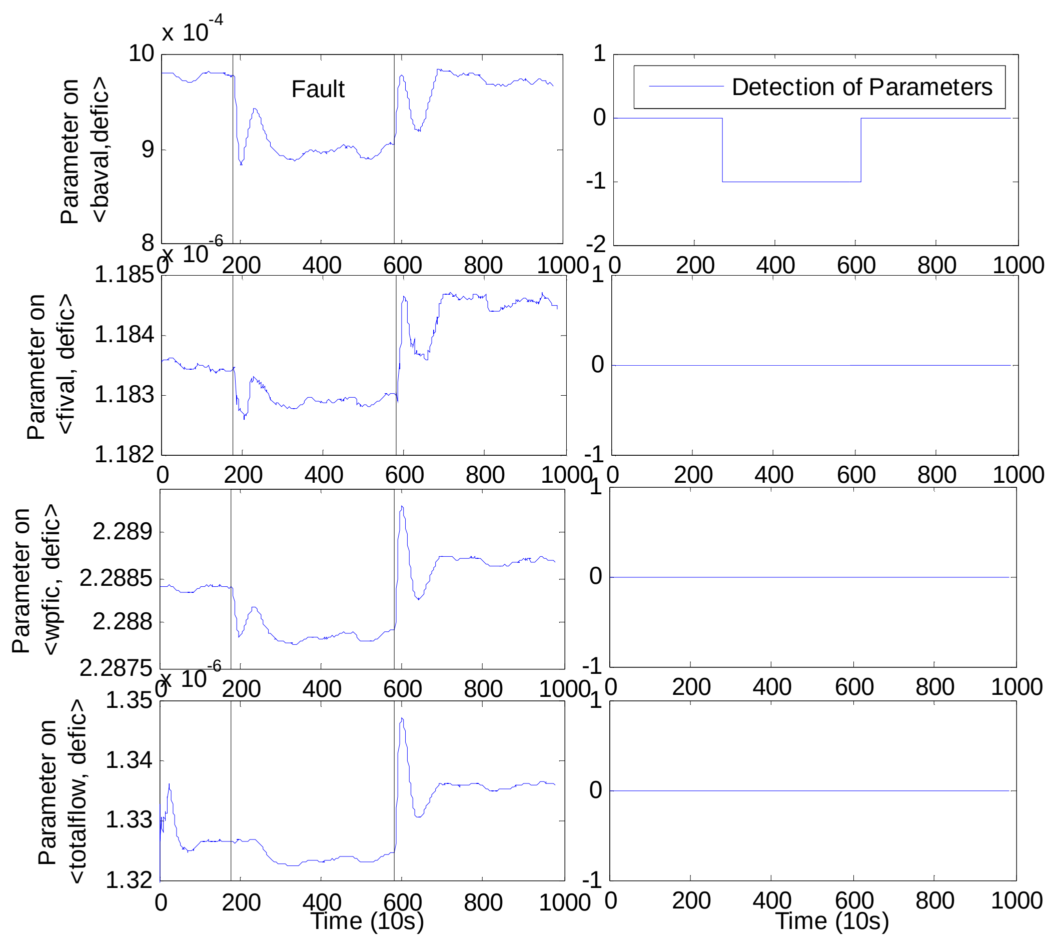

Fig.3. Updated parameters for *de_fic* by Kalman filter

The Kalman filer was use to update the parameters on the arcs <*baval*, *de_fic*>, <*fival*, *de_fic*>, <*wp_fic*, *de_fic*>, and <*totalflow*, *ash*> after the results in Figure 2 was obtained. The parameter signals were also evaluated by CUSUM method to detect the changes. The minimal detectable change was set up as 10% of the original value. The example for the four parameters for variable *de_fic* is shown in Figure 3.

The change of the parameter on the arc <*baval*, *de_fic*> implies that the process components located on that arc are suspected to be faulty. The faulty component in this case was identified to be the basis weight valve.

5. DISCUSSIONS

The proposed method combines the causal digraph method and the Kalman filter and utilizes the advantages of both of them. In the method, the causal digraph is used to locate the fault on the interesting variables and the Kalman filter is responsible to find out the faulty arcs for the faulty nodes by updating the parameters of the arcs. The results of the test on the paper machine short circulation process shown in the paper proved that the method is able to locate the fault on the arcs and in turn leading to the faulty process component, which provides much more information for the fault diagnosis.

In this case static models were used to represent the cause-effect relationships. The use of dynamic models together with parameter tracking is a topic for future research

ACKNOWLEDGEMENTS

This work is finically supported by the Finnish Technology development agency (TEKES). Authors are also very grateful to the Technical Research Centre of Finland (VTT) for providing the advanced paper machine simulator (APROS) as testing platform of the developed method.

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ESTIMATION OF 2-DIMENSIONAL VARIATION ON THE BASIS OF IRREGULARLY MOVING SCANNING SENSOR

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Abstract: This paper presents a 2-dimensional simulator mimicking quality variations on paper machines and their measurement with a scanning gauge. The simulator includes web forming, measurement of a quality parameter, estimation of spatial and temporal variations and estimate based wed controls. In the simulator, a paper web can be measured so that the scanning sensor's movement in the frame can be chosen arbitrarily. The simulator proves a tool to research the influence of the sensor movement to estimation and control of the paper web quality.

Keywords: paper web, quality variation, quality measurements, estimation, quality control, simulation.

1. INTRODUCTION

Traditionally, the quality of a paper web is measured by a sensor that is mounted on a frame. The sensor scans regularly back and forth over the web while the web is moving underneath it in which case the sensor draws a zig-zag measurement path to the web (Fig. 1). From the on-line measurements the 2-dimensional variation is estimated. Variations in the web are divided into tree categories: spatial, temporal and residual variations. Spatial and temporal variations have separate control systems: thus the 2-dimensional variation has to be separated into spatial and temporal components. Residual variation is normally not estimated and cannot be controlled.

Despite the development of new measuring systems, the single scanning sensor continues to be the predominant measurement system in the paper making industry. Given that the sensor takes measurements from only a small fraction of the sheet it is necessary to estimate the variations that are not seen by the sensor to control variations over the whole web. Generally, in estimation it is assumed that the temporal variations are much more rapid than spatial variations and are assumed to influence

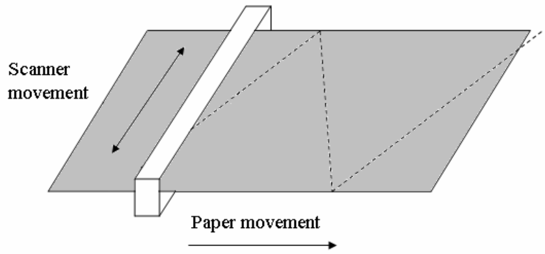

Fig. 1. A zig-zag measurement path

all spatial locations. The spatial profile can be considered nearly time invariant and only spatial control affects it. Without this assumption, the decomposition of the variations into spatial and temporal components would be meaningless.

Typically the scanning sensor moves at a constant speed. Moving the sensor irregularly provides a possibility to get additional information about web quality variations and it could improve the separation of spatial and temporal variations, for example when temporal variation is fast compared to scan time or when tilted quality variations occur. Furthermore, irregular sensor movement may provide a means for occasional estimation of spatial actuator responses during normal operation. Because the web is controlled based on the estimates of spatial and temporal variations, scanner movement can be seen as an unused degree of freedom in control.

Current scanner systems calculate the spatial estimate as a fixed window average of last 6-10 scans or exponentially weighted moving average (EWMA) filter over scans. Temporal estimate is the average of the spatial estimate at each time instant. Such an estimation method has several known problems: for example with periodical temporal variation when variations periodic time is near the sensor scan time. The estimation method is not directly suited for irregular scanning. For example, when the sensor is stopped for a while or when the movement direction of the sensor is changed in the middle of the web, the control must be put on manual.

Estimation and separation of the spatial and temporal components have been intensively researched for some three decades. There have been many attempts to solve the estimation problems by using methods, such as wavelets (Dumont et al. 2004), model-based (Dumont et al. 2004, Wang et al. 1993) and frequency domain approaches (Duncan and Wellstead 2004).

2. SIMULATOR

We present a simulator for 2-D quality variations of the paper web. The output variation is a combination of user defined variation components and simulated actions of spatial and temporal controls. User may define an arbitrary movement of the sensor and the estimation of 2-D variation and separation to spatial and temporal components is carried out based on this measurement path.

At present the simulator is for one quality variable only: in particular, we consider basis weight or dry weight. Nonetheless, the used model does not exclude using the simulator for some other quality variable as well. The 2-D variation is presented as a matrix in which one cell is describing one centimetre in spatial direction and one second in temporal direction of a real paper sheet.

Controls are implemented in a quite simplified form and idealized. The CD controls take action at user-specified intervals.. The spatial component is controlled with a slice screw response model. The actuators responses are assumed to be identical and web shrinkage is neglected. The optimal CD control action is determined unconstrained in steady state as

$$\Delta u = \left(B^T B\right)^{-1} B \Delta y \tag{1}$$

where

Δu is the change in control actions,

Δy is deviation from setpoint and

B is the actuator-to-CD response matrix.

Only a part of the optimal actuator change is implemented in one control step (default 10 %) which is roughly describing the dynamics and also the conservative way to control. The temporal component is controlled with second order PI-control with delay mimicking the feeding pump. The controllers parameters, gain and integration time, are derived using lambda tuning with time constants of 10 and 20 seconds and delay of 30 seconds. Lambda is chosen three times bigger than the delay. This makes the control rather slow but robust.

At this point the control models are identical with the simulation response models. However, currently our interest is more in the estimation than in the controls of the paper web.

The simulator provides as results the simulated quality variation, estimated quality variations and their variances and the estimate separated into spatial and temporal variations. In addition it gives the spatial and temporal control actions and the effect of the controls.

The simulator has been made modular to enable easy development and modifications of the functionality of the simulator in the future, in particular for testing alternative estimation methods.

3. ESTIMATION

The estimation method in the simulator updates spatial and temporal estimates at each time instant by combining new measurement information to previous estimate information according to Bayesian theory. Both measurements and estimates are described as Gaussian probability densities having the expectations as the values and the variances describing the uncertainties. Measurements are assumed non-biased. Because of the moving sensor, spatial points are measured at non-uniform time steps. That is taken account by choosing the system model with a set of independent random walks at each spatial location, with a uniform diffusion constant D. This means that the variance of an estimate is increasing linearly in time, when the point is not measured. Obviously, random walk model is unrealistic, for example such a system would not be controllable as the variances of uncontrollable modes would continue to increase indefinitely. However, we use the random walk model as a "worst-case" disturbance model and for estimation only.

The web estimate of a quality variable $\hat{x}(i, j)$ is computed from the sensor measurements and position signals. Due the scanning measurement, only few of the spatial points are measured at any time instant. For points that are not measured, according to the random walk model the updated estimate is the previous estimate and the variance is increased with $D\Delta t$.

$$\hat{x}(i,j) = \hat{x}(i-1,j)$$
$$\hat{\sigma}^2(i,j) = \hat{\sigma}^2(i-1,j) + D\Delta t \tag{2}$$

where
$\hat{x}(i,j)$ is the value of web estimate,
$\hat{\sigma}^2(i,j)$ is the variance of the quality estimate
$D\Delta t$ is the random walk diffusion in one time step.

At positions that are measured during the time step the new estimate is a Bayesian combination of previous estimate and new measurement and is given as:

$$\hat{x}(i,j) = \frac{\left(\hat{\sigma}^2(i-1,j) + D\Delta t\right) x_{meas}(i,j) + \sigma^2_{meas}\hat{x}(i-1,j)}{\sigma^2_{meas} + \hat{\sigma}^2(i-1,j) + D\Delta t} \tag{3}$$
$$\hat{\sigma}^2(i,j) = \left(\frac{1}{\hat{\sigma}^2(i-1,j) + D\Delta t} + \frac{1}{\sigma^2_{meas}}\right)^{-1}$$

where
$x_{meas}(i,j)$ is the value of the measurement and
σ^2_{meas} is the measurement uncertainty.

The temporal estimate $\hat{x}^{temp}(i,j)$ is the mean value of the web estimate $\hat{x}(i,j)$ over spatial index j,

$$\hat{x}^{temp}(i,j) = \frac{1}{M}\sum_{j=1}^{M}\hat{x}(i,j) \tag{4}$$

and spatial estimate $\hat{x}^{spat}(i,j)$ is the web estimate with temporal estimate subtracted.

$$\hat{x}^{spat}(i,j) = \hat{x}(i,j) - \frac{1}{M}\sum_{j=1}^{M}\hat{x}(i,j) \tag{5}$$

This estimate can be interpreted as EWMA with nonuniform sampling and random walk degradation of prior information. Hence, in spite of its simplicity it is a natural extension of current practice both for regular and irregular scanning.

3.1 General process model

The Bayesian estimation method above can also be understood as a Kalman filter with process model:

$$x(k+1) = x(k) + \sum_{i=0}^{d-1} G(k,i)u(k-i) + v(k)$$
$$E\{v(k)\} = 0 \quad \forall k \tag{6}$$
$$E\{v(k)v(l)^T\} = R(k)\delta_{kl}$$

with

$$\sum_{i=0}^{d-1} G(k,i)u(k-i) = 0 \tag{7}$$
$$R(k) = D\Delta t \cdot Id$$

Where Id is the identity matrix

The ideal measurement over full width of the web at time instant $k+1$ is described as:

$$y(k+1) = x(k+1) + e(k)$$
$$E\{e(k)\} = 0 \quad \forall k \tag{8}$$
$$E\{e(k)e(l)^T\} = Q(k)\delta_{kl}$$

where $Q(k)$ is the ideal measurement variance matrix.

Because of the real measurement mode all spatial positions are not measured at any time instant. Let $M(k+1)$ be the set of measurements at time instant $k+1$, so that the collection $\{M(k+1)\}_k$ is a description of the scanner movement. The accuracy matrix $A(k)$ of scan measurement is calculated by masking the accuracy matrix of ideal measurement $Q(k)^{-1}$ with $M(k+1)$ as

$$m(k+1)_i = \begin{cases} 1 & i \in M(k+1) \\ 0 & i \notin M(k+1) \end{cases} \tag{9}$$
$$A(k) = Q(k)^{-1} \otimes \left(m(k)m(k)^T\right)$$

Here $\otimes$ denotes element-by-element multiplication of matrices.

With the presented model the forecasting and the estimation is as:

$$\hat{x}(k+1|k) = \hat{x}(k|k) + \sum_{i=0}^{d-1} G(k,i)u(k-i)$$
$$P(k+1|k) = R(k) + P(k|k)$$
$$\hat{x}(k+1|k+1) = P(k+1|k+1)\cdot ... \tag{10}$$
$$\left(P(k+1|k)^{-1}\hat{x}(k+1|k) + A(k+1)y(k+1)\right)$$
$$P(k+1|k+1)^{-1} = P(k+1|k)^{-1} + A(k+1)$$

which is a form of the regular Kalman filter.

Form (10) shows that with process model (6), the simple Bayesian estimation method can be easily extended to incorporate the effects of the controllers. Such estimation methods have been reported in literature, but current commercial systems appear not apply them.

Note that the random walk structure of (6) differs from the models for control. Similarly to what was discussed about the simple model (2)-(3), also here the model is intended only for observation and thus worst-case dynamics has been chosen. Choosing $G(k,i)$ as time difference of impulse response function, regular response functions are obtained.

Because the temporal variation can be considered as noise to the estimation of spatial variation, the noise model *R(k)* could be extended with a second term that introduces a random effect common to all positions in *j*. Then the noise model would be:

$$R(k) = D\Delta t \cdot Id + \sigma_{temp}^2 \cdot I \tag{11}$$

where

σ_{temp}^2 is noise term for temporal variations and

I is matrix of ones.

With this added tuning parameter we may choose how we interpret deviation from priori forecast: how much of it is temporal and how much residual.

4. RESULTS

In this section, two examples of simulation results are presented. In the first example the estimation is done with the basic Bayesian estimation method (2)-(3) and the second with the Bayesian method with extended noise model (11).

The web is measured along a path where in the first 50 time steps the scanner is moved 50 spatial positions per time step (50 cm/s), for next the 50 time steps the scanner speed is 40 and so on until the scanner is stopped for 50 time steps and then it starts over with speed 50 slowing down similarly. The scanner path is presented in Fig. 2. The variances of the web quality estimates do not depend on the estimates but only the scanner path. The variances for the scanner path are shown in Fig 3. The scanner path is visible as sudden reductions at variances.

Input variations are sinusoidal with white noise for both spatial and temporal directions. In addition there is white noise as residual variation for the whole web. The spatial width is 500 points (cm) and temporal length is 600 time steps (s). The spatial and temporal controls take actions at every 20 time steps.

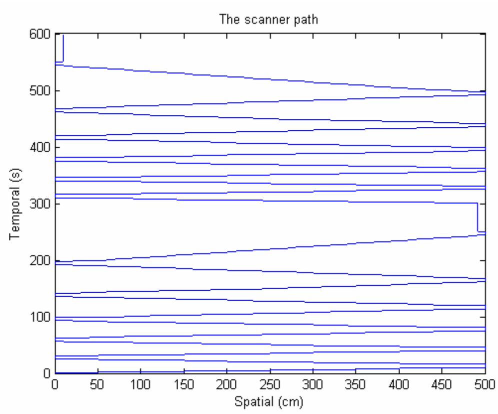

Fig. 2. The scanner path

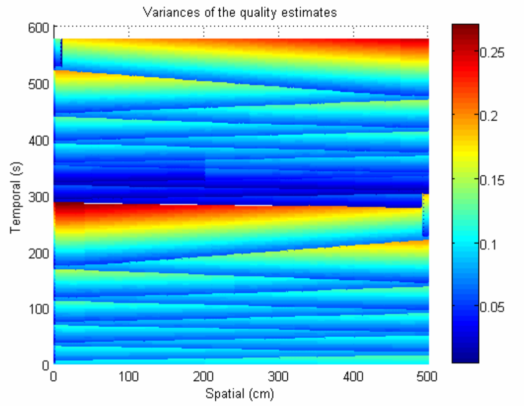

Fig. 3. Variances of the estimated quality estimates

4.1 Bayesian estimation method

The first simulation example is done with the presented Bayesian estimation method (2)-(3). The random walk diffusion constant $D\Delta t$ = 0.002 and the variance of the measurements σ_{meas}^2 depends on the scanner speed, but is roughly 0.1.

The simulated quality variations are shown in Fig. 4(a) and the quality estimates in Fig 4(b). In the beginning of the simulation, the initialized spatial variation is clearly visible, but after 200 time steps the spatial control has damped variations. Due the slow temporal control, its effects are not so visible. The scanner path is visible in estimates as the change points of the estimates. Fig. 5 presents the estimated quality variations separated into (a) spatial and (b) temporal variations. In Fig. 5(b) the temporal estimate is drawn with blue and the webs real temporal variation with red. Because the presented Bayesian estimation method updates the temporal estimate as the mean of the web estimate, the temporal estimate follows slowly true variation. This is stressed especially with slow scanner speeds since the web estimate is updating slowly too. Due the estimation method, errors in temporal estimates reflect to spatial estimates too.

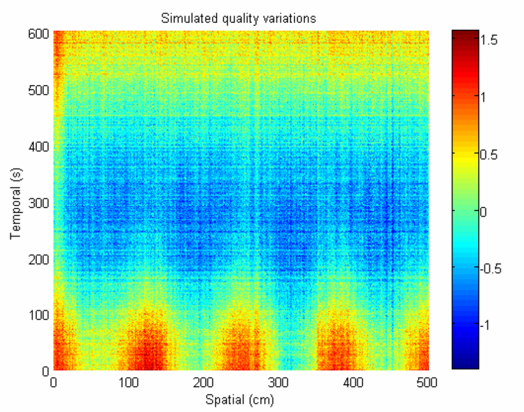

Fig. 4(a) Simulated quality variations using Bayesian estimation method

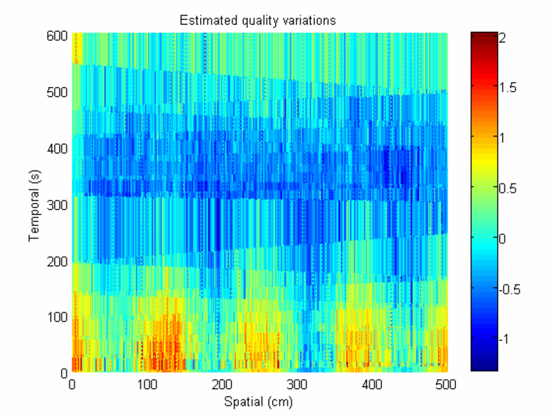

Fig. 4(b) Estimated quality variations using Bayesian estimation method

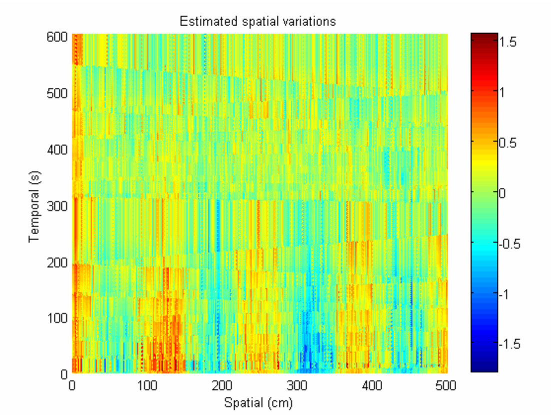

Fig. 5(a) Spatial estimates using Bayesian estimation method

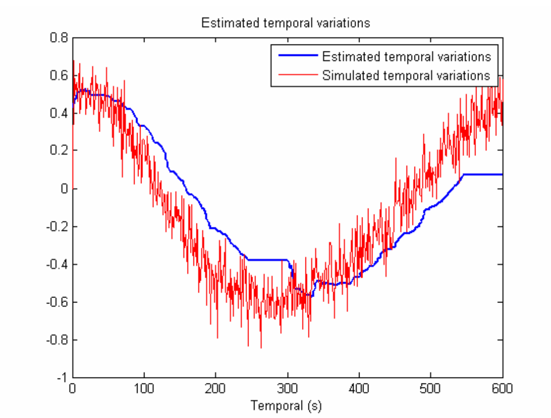

Fig. 5(b) Temporal estimates using Bayesian estimation method

4.2 Bayesian estimation method with extended noise model

The second simulation example is done using the extended noise model (11) in Bayesian estimation method. The parameters of the noise model are chosen as: $D\Delta t = 0.00195$ and $\sigma^2_{temp} = 0.00005$, so the sum of the parameters is equal to diffusion constant used in the earlier example.

Fig. 6(a) shows the simulated quality variations and 6(b) the estimated quality variations. Fig. 7 shows the (a) spatial and (b) temporal estimates. The biggest improvement is seen in the temporal estimate. The estimate follows much better the webs real temporal variation, even with slow scanner speeds. That is causing better control results. The extended noise model also reduces noise from spatial estimates.

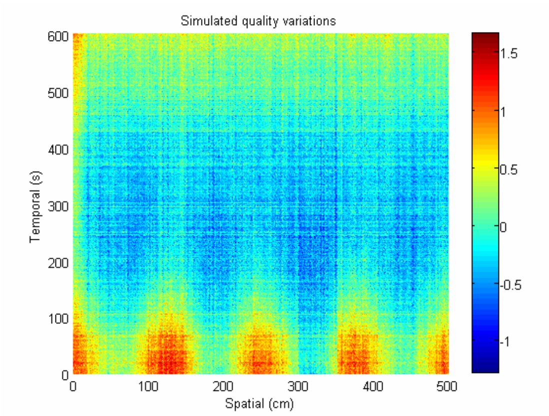

Fig. 6(a) Simulated quality variations using Bayesian estimation method with extended noise model

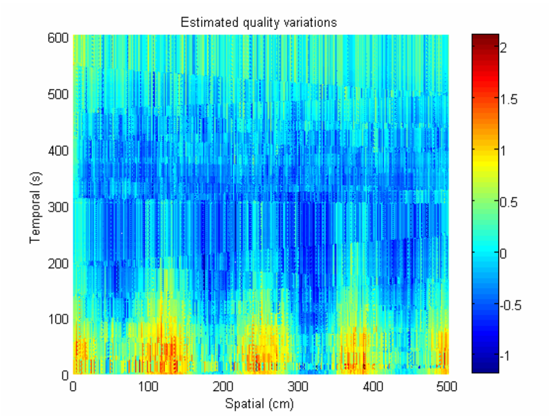

Fig. 6(b) Estimated quality variations using Bayesian estimation method with extended noise model

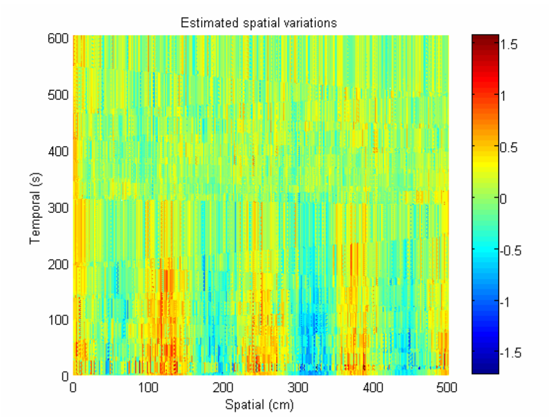

Fig. 7(a) Spatial estimates using Bayesian estimation method with extended noise model

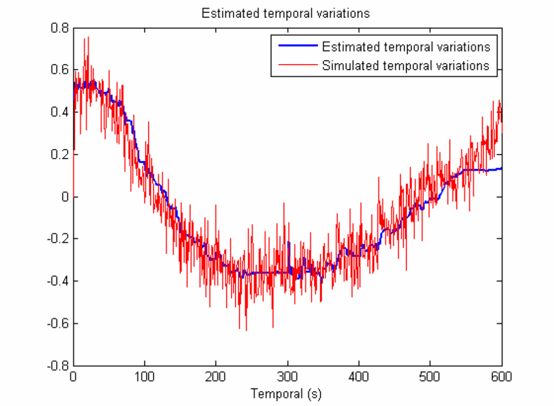

Fig. 7(b) Temporal estimates using Bayesian estimation method with extended noise model

5. CONCLUSIONS

The simulator provides a tool for researching the effects of the scanner movement to the estimation and control of 2-dimensional variations. The quality control in the paper machine is based on spatial and temporal estimates. Therefore the quality of the estimates affects directly to the quality of manufactured paper.

By modifying the scanner movement in the frame, it is possible to obtain additional information about the web quality variations by concentrating measurements on interesting parts of the web. For example, when the sensor is stopped, the measurement information is purely temporal variations. Also in case, when there are not temporal variations or the variations are known, the sensor stopping provides opportunity to estimate online spatial control responses.

Our long term goal is to find the dynamically optimal measurement path. In this case, the optimal can be thought as optimal in terms of variances of the estimates, meaning that the best possible knowledge of the web quality variations, or even as so that the effects of the controls are as good as possible. The control effect optimization in respect of the measurement path *M(k)* is a really complex optimization problem. Including measurement selection into optimal information extraction (Mehra, 1976) or into optimal control (Meier III et al, 1967) has been studied in literature but is with few applications so far. With the process model (6) the optimal path is the regular scanning path. Therefore irregular scanning will be triggered by spatially non-uniform or time-varying noise term, or by need to estimate response models during normal operation.

6. ACKNOWLEDGMENT

This work was supported by NoTeS project belonging to MASI programme of TEKES (Finnish Funding Agency for Technology and Innovation) and in part by SyDeMIS project that is funded by Academy of Finland.

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14 TH NORDIC PROCESS CONTROL WORKSHOP
AUGUST 23 – 25, 2007
HELSINKI UNIVERSITY OF TECHNOLOGY, ESPOO, FINLAND

IMPROVING PROFILE ESTIMATION ON PAPER AND BOARD MACHINES

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Abstract: Traversing scanners are still widely used in the online measurement of product quality variables on paper and board machines. A traversing scanner measures from a zig-zag path. The feedback control is only possible separately in machine direction (MD) and cross direction (CD) and thus the scanner measurement data has to be separated into MD and CD components. New profile estimation methods, such as Bayesian, Kalman filter based and ARMA model related, have been developed. The functionality and performance of new CD and MD profile estimation methods in CD and MD control in simulations are discussed.

Keywords: Profiles, variability, estimation, Kalman filters, ARMA models, probabilistic Bayesian, simulation, power spectra, paper industry.

1 QUALITY MEASUREMENT AND CONTROL ON PAPER AND BOARD MACHINES

The product quality is described with quality variables, such as basis weight, moisture, caliper, ash content and many others in paper and board industry. There is some variability in product quality variables. The whole web width sensing devices are available only for some quality variables. Quality variables are most often measured online by the sensors of traversing scanners, which implies sparse measurement data from a zig-zag path. Real CD profiles in cross direction are not available. The CD and MD profiles have to be estimated for control purposes (Figure 1).

The quality variations are attenuated separately in cross and machine direction by closed CD and MD control loops. The paper and board quality variables - basis weight, moisture, caliper, ash, color, gloss and fibre orientation - may be measured online and controlled automatically in machine direction. The periodic measurement principles of traversing scanners and remote actuator positions from measuring devices imply long time delays. Model predictive control (MPC) algorithms are often used.

Basis weight, moisture, caliper, coat weight and fibre orientation may be controlled automatically in cross direction. Optimization computing is utilised in large-scale multivariable CD control algorithms for hundreds of measurement points and dozens of actuators to minimise a CD profile error.

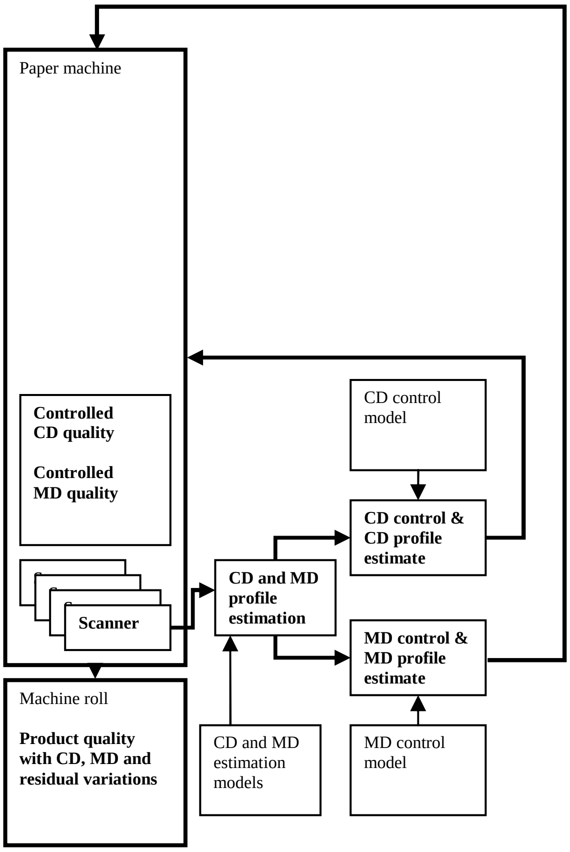


Fig. 1 Scanner measurement data has to be separated into CD and MD profiles for the CD and MD control loops by the profile estimation.

2 MEASUREMENT PROFILE ESTIMATION

During the last twenty years there have been some attempts to improve the CD and MD profile estimation of scanner measurement data, for example in [Wang, et. al., 1993], [Dumont, et. al., 2004] and [Gopaluni, et. al., 2006]. The role of profile estimation in the functionality and performance of quality control applications is still very interesting. The role of automation for the dependability performance in production plants is significant.

In this study the profile estimation is approached with probabilistic and time series estimation methods. The variability of a paper quality variable may be presented with the help of a mean value, variations in CD and MD and a residual variation:

(Eq. 2.1)

$$q(i,j) = q(i,j)_{av} + e(i,j)^{CD} + e(i,j)^{MD} + e(i,j)$$

- $q(i,j)$ the variable value in a row i (CD), in a column j (MD), in a web matrix
- $q_{av}(i,j)$ the mean value of all web matrix elements
- $e(i,j)^{CD}$, $e(i,j)^{MD}$, $e(i,j)$ the CD, MD and residual variations, in a web matrix.

In traditional commercial quality control systems, in CD profile estimation, single scans are updated exponential by previous filtered scans. These scans are averaged sliding in order to decrease the MD variation effect on the CD variation. The MD profile estimate values come from single scan values by averaging.

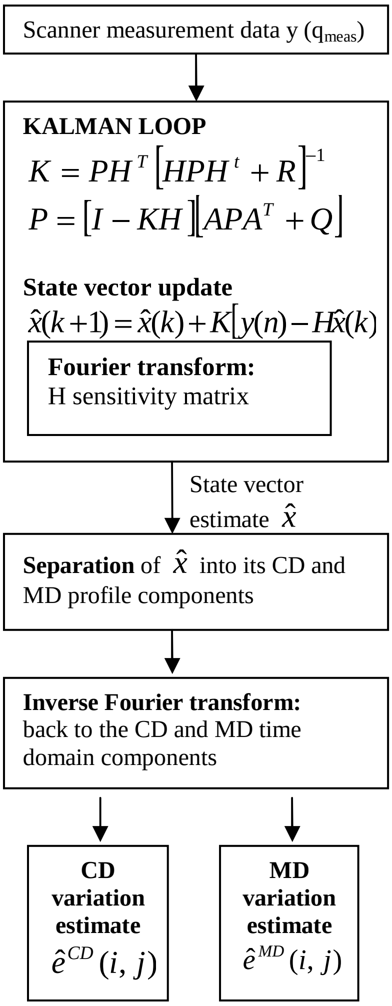
2.1 Bayesian Method

The Bayesian method is based on the Bayesian rule. The probability density functions of quality variables are assumed to be normal distributed, although this is not always the fact. If the quality variables are normal distributed, the variation of a quality variable can be described by the time dependent expectation (mean value) and the variance, related to the uncertainty of the variable estimate. A random walk model is applied in the estimation for the irregular sampling: the uncertainty of the estimate increases when the measurement matrix point is not measured. A detailed description of the Bayesian estimation method is presented in the NPCW07 conference paper of [Ylisaari et. al., 2007].

2.2 Kalman Filter Method

A Kalman filter can be considered as a special case of probabilistic Bayesian estimation. A Kalman filter has previously been used for the CD and MD profile estimation in [Wang et. al., 1993], but commercial applications do not follow. The new idea introduced is the utilization of Fourier components as a state vector in a Kalman filter. The Fourier components represent quality variable variations in CD and MD. The frequencies of those Fourier components have to be defined beforehand: usually the controllable frequencies are used. The Kalman filter estimator also needs the initial information on the quality variable measurements noise level. After this, the Kalman filter can calculate the CD and MD profile estimation based on the measurement data *y*. The Kalman filter updates the error covariance and the state vector according to the basic, well-known Kalman equations (Figure 2). As a result, the updated state vector x is calculated, which contains the Fourier components in both CD and MD.

There is one fundamental difference in the Kalman estimator compared to the other estimators. After each measurement, not only the CD estimate and MD estimate at this current time step are achieved, but also the future MD trend is available. This is due to the fact that the Fourier components are used to represent the variations in CD and MD. This may give an advantage to the control systems of paper machines. How to utilise the predicted MD profile in the control strategy is under development.



y the quality variable measurement data vector
x the state vector with the Fourier components
P the error covariance matrix
K the Kalman gain matrix: statistically optimal weights for the state vector components
H the measurement sensitivity matrix: the inverse Fourier transform operator
A the model matrix: a phase shift operator for the state vector
Q the covariance of the state vector: the noise level of the model
R the variance of the measurement data: the noise level of the measurement

Fig. 2 In the Kalman filter based estimation the frequency domain state vector is updated in a Kalman filter based loop.

2.3 Autoregressive Moving Average Approximation Method

Autoregressive moving average (ARMA) modeling may be used for stochastic parameter estimation in profile estimation. After every new measurement point from a scanner the new MD and CD estimates are computed. An ARMA model is used for the MD variation estimates:

(Eq. 2.2)
$$\hat{e}^{MD}(i, j) = y^{MD}(i, j) + \phi_1 \hat{e}^{MD}(i, j-1) + \phi_2 \hat{e}^{MD}(i, j-2)$$

y^{MD} the web measurement variation in MD
Φ_1, Φ_2 the ARMA model coefficients, computed from autocorrelation functions.

The CD variation estimates for measured points of a web are computed by exponential filtering:

(Eq. 2.3)
$$\hat{e}^{CD}(i, j) = \alpha \cdot y^{CD}(i, j) + (1-\alpha) \cdot \hat{e}^{CD}(i-1, j)$$

The CD estimates for not measured points in a web are computed by updating the previous estimates by estimation errors:

(Eq. 2.4)
$$\hat{e}^{CD}(i, j) = \hat{e}^{CD}(i-1, j) + \beta \cdot (y^{CD}(i, j) - \hat{e}^{CD}(i-1, j))$$

y^{CD} the web measurement variation in CD
α, β the updating coefficients computed by a gradient method.

3 SIMULATION RESULTS

The developed estimation methods Bayesian, ARMA and Kalman seem to have some advantages over the commercial, traditional one. The power spectra of Bayesian, ARMA, Kalman and traditional methods have about the same disturbance attenuation performance in CD control loops (Figure 3). The wavelengths under 20 cm cannot be attenuated at all. The actuator spacing is assumed to be 10 cm and the CD control is based on a simple quadratic optimisation algorithm.

The Kalman method looks better than others in the profile separation. The Bayesian method has difficulties in profile separation, when the machine direction variation is high. This leads to situations when the CD estimate results some MD variation and the CD control loop tries to attenuate this mistaken MD variation. The Kalman method has a good separation performance also with high frequencies in MD. The ARMA estimator can track high frequencies efficiently, too. In these simulations real industrial quality measurement variations are utilised.

The Kalman estimator code needs about three times and the Bayesian two times as much computing time compared with the ARMA code. Time delays and time constants in CD and MD control loops are dozens of seconds or even minutes and in quality control systems the common execution cycles of MD and CD control codes are several seconds. The execution time of improved estimation methods does not restrict the usage of advanced estimation methods in real-time CD and MD control applications.

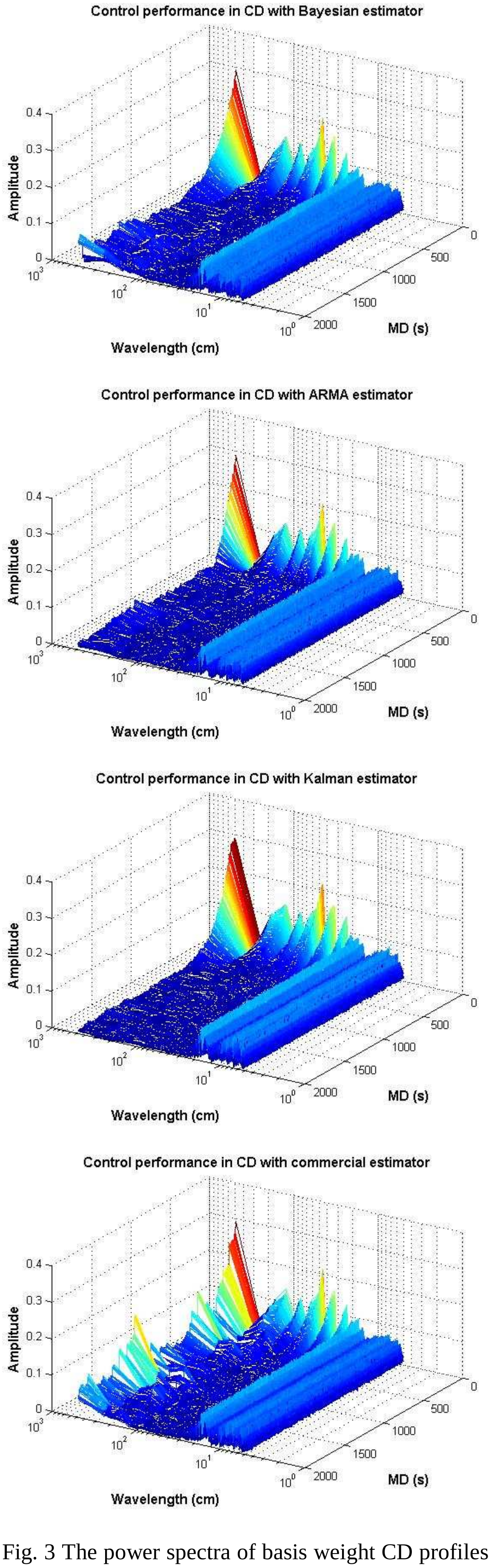


Fig. 3 The power spectra of basis weight CD profiles with Bayesian, ARMA, Kalman and commercial estimators, presented in time domain, show the attenuation of CD wavelengths bigger than 20 cm.

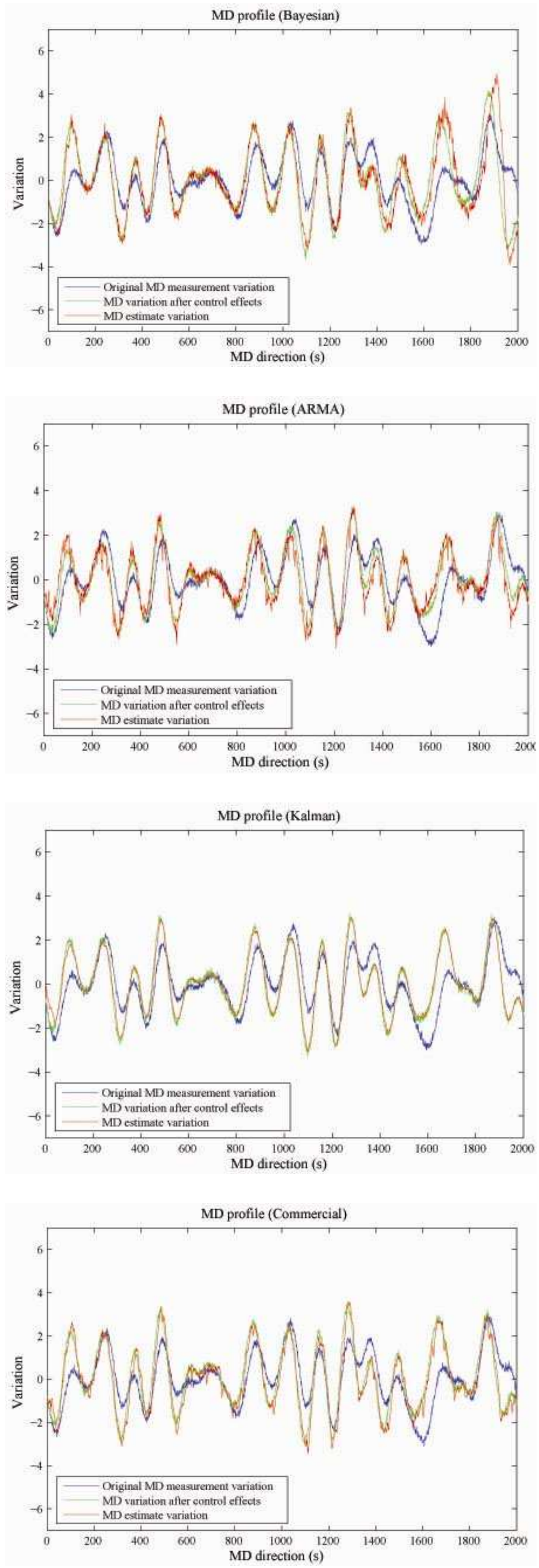


Fig. 4 The MD estimate variation and the resulting MD variation after control effects of basis weight with Bayesian, ARMA, Kalman and commercial estimators, presented in time domain, have the same oscillation trend with the original variation.

In the MD control the simulator gives an oscillation with a period of 150 seconds, following the original measurement variation (Figure 4). The variations in the MD estimates and in the resulting MD profiles are bigger than in the original measurement signals.

This may be partly due to insufficient MD control algorithm tuning. The simulation results with the Bayesian, ARMA, Kalman and commercial estimators are rather similar. In the MD control, the process model is described with two time constants of 10 and 20 seconds, and with a time delay of 30 seconds. A simplified model predictive control algorithm is used.

4 CONCLUSIONS

According to simulations the CD and MD profile separation in quality control systems may be improved by advanced estimation methods. In CD control the variations can be attenuated better than with conventional commercial methods. Especially, the Kalman filter based estimation results a good performance against the disturbances of a wide range and with different scanning speeds. The tuning of MD control algorithms for the new estimation methods has to be developed further.

ACKNOWLEDGEMENTS

The quality control simulator has been developed in co-operation of the TUT Measurement and Information Technology, the LUT Applied Mathematics and the KyAMK Automation laboratory, and funded by the national TEKES MASI program, in the NoTeS project, under the guidance of prof. Risto Ritala.

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COMPENSATING THE TRANSMISSION DELAY IN NETWORKED CONTROL SYSTEMS

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Abstract: Recent interest in networked control systems (NCS) has instigated research in both communication networks and control. Analysis of NCSs has usually been performed from either the network or the control point of view, but not many papers exist where the analysis of both is done in the same context. In this paper an overall analysis of the networked control system is presented. First, the procedure of obtaining the upper bound delay value for packet transmission in the switched Ethernet network is presented. The upper bound delay algorithm applies ideas from network calculus theory. Next, the obtained delay estimate is utilised in delay compensation for improving the Quality of Performance (QoP) of the control systems. For the improvement of the performance a robust control based delay compensation strategy is used.

Keywords: Networked control systems, delay compensation, real time systems

1. INTRODUCTION

Automation systems of the future and even those currently in use today, will consist of a large number of intelligent devices and control systems connected by local or global communication networks. In these Networked Control Systems (NCSs), communications between process, controllers, sensors and actuators are performed through the network.

In most cases, the insertion of the network does not significantly affect the performance of the control system. However, for some time constrained systems (constraints coming from the dynamic of the physical process to observe and to control), the implementation of the NCS should be done considering the implications introduced by the network. For such systems, the insertion of the communication network into the feedback control loop introduces an additional delay, either constant or time varying, that makes the analysis and the control design more complex.

Studying the networked control systems requires the evaluation of the Quality of Service level provided by the network and integration the values of these QoS parameters in the control design. One of the main limitations of the previous research on NCS is the lack of integrated control design and network evaluation. It is often assumed that either the control is specified (information timing constraints exists) or the performance of the network is well-defined (information about the delay distribution, uncertainty, deviation from mean value, missing value rate is assumed known). The results for the whole design cycle, where the network evaluation and control are integrated and performed the same context, are still lacking.

In this paper the whole design cycle for the NCS will be presented. A novel integrated approach will be presented where the estimated information about the network performance will be utilized in the control synthesis. First, the procedure of obtaining information about the delay (the upper bound delay) is presented and the obtained value is utilised in delay compensation. The delay algorithm presented applies ideas from network calculus theory, and the delay compensating strategies is based on robust control theory.

The paper is organized as follows: Chapter 2 is dedicated to introducing the upper bound delay estimation algorithm for the switched Ethernet network. In Chapter 3 the delay compensation strategy is introduced. Chapter 4 consists of the simulation results and discussion, and the paper ends with a concluding section in Chapter 5.

2. UPPER BOUND DELAY ESTIMATION

In the paper the switched Ethernet network is used as an example of the NCS network. The Ethernet networks are nowadays also more and more used in control applications and, in this context, it is important to understand the behaviour of the network in order to be able to control the network performance, such as delays (Georges et al., 2004). Next, the procedure of obtaining the upper bound delay over the network will be explained. The algorithm presented applies ideas from network calculus theory (see Cruz, 1991; Le Boudec and Thiran, 2001; Jasperneite et al., 2002). For more details of the algorithm, see Georges et al. (2005). First, the method to obtain a maximum delay for crossing a single Ethernet switch will be explained in Section 2.1, and the procedure of obtaining end-to-end delays in the network, based on the delays over the switches, will be given in Section 2.2.

2.1 Maximum delay for crossing the Ethernet switch

The first step in the Ethernet switch modelling is determination of an upper bound delay for crossing each of the basic components: FIFO multiplexer, FIFO queue, and demultiplexer. The upper bound delay over the switch is then the sum of the upper bound delays over these basic components, Figure 1:

$$\overline{D_{switch}} = \overline{D_{mux}} + \overline{D_{queue}} + \overline{D_{output}} \tag{1}$$

where the notation $\overline{D}$ is used to represent the upper bound value of the delays.

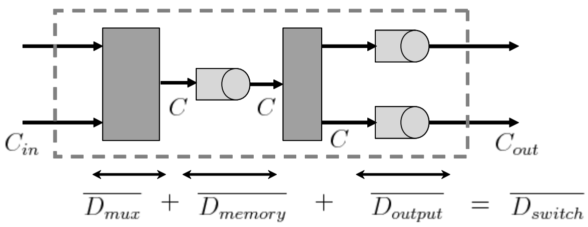

Fig. 1 Model of a 2 port-switch in a full duplex mode based on shared memory and a cut-through management.

In the mathematical analysis, the traffic arriving at the switch, both periodic and aperiodic is modelled as a 'leaky bucket controller'. Data will arrive at the leaky rate only if the level of the bucket is less than the maximum bucket size. Traffic models are called the arrival curve in network calculus theory and, with the assumption that the traffic follows the leaky bucket controller and the incoming rate is limited by the port capacity, these curves are affine and have the form of:

$$b(t) = \min(C_{in}t \quad \sigma + \rho t) \tag{2}$$

where σ is the maximum amount of data that can arrive in a burst, ρ is an upper bound of the average rate of the traffic flow, and C_{in} is the capacity of the input port. In the same way, service curves are used to represent the minimal data processing activity of the components. Typical arrival and service curves are shown in Figure 2.

The approach is based on the evolution of a specific parameter, the backlog. The backlog is the number of bits waiting in the component, and it is a measure of congestion over the component. For the arrival curves in Figure 2, the upper bound backlog occurs at time t where the following line is a maximum:

$$b_1(t) + b_2(t + L / C_2) - C_{out}t \tag{3}$$

where b_1 and b_2 are the arrival curves of stream 1 and 2 at time *t*, *L* is the maximum length of the frames, C_2 is the capacity of the import port 2, and C_{out} is the capacity of the output link. When the upper bound backlog over the component is known, the upper bound delay over the component is then obtained by dividing the maximum backlog value by the capacity of the output link of the multiplexer. In a FIFO m-inputs multiplexer, the delay for any incoming bit from the stream *i* is upper-bounded by:

$$\overline{D_{mux,i}} = \frac{1}{C_{out}} \min_k \overline{B_{mux,k}} \tag{4}$$

where $\overline{B_{mux,k}}$ is an upper-bound of the backlog in the bursty periods u_k, such that $1 \le k \le m$. For *k* = *i*, the bursty period is defined by $u_i = \sigma_i / (C_i - \rho_i)$ and the backlog is upper-bounded by :

$$\overline{B_{mux,i}} = \sum_{z=1;z\neq i}^{m} \left(\sigma_z + \rho_z \left(u_i + \frac{L_z}{C_z} \right) \right) + u_i (C_i - C_{out}) \tag{5}$$

where σ_i is the burstiness of the stream *i*, ρ_i is the average rate of arrival of the data of stream *i*, L_i is the maximum length of the frames of stream *i*, and C_i is the capacity of the import port i. For $k \neq i$ such that $1 \le k \le m$, we have $u_k = \sigma_k / (C_k - \rho_k) - L_k / C_k$ and

$$\overline{B_{mux,i}} = \sum_{z=1;z\neq k}^{m} \left(\sigma_z + \rho_z \left(u_k + \frac{L_z}{C_z} \right) \right) + u_k (C_k - C_{out}) - \rho_i \frac{L_i}{C_i} + L_k \tag{6}$$

For the FIFO queue the delay of any byte is upper-bounded by:

$$\overline{D_{queue}} = \frac{1}{C_{out}} \frac{(C_{in} - C_{out})}{C_{in} - \rho_{in}} \sigma_{in} \tag{7}$$

For the demultiplexer it is assumed that the time required to route the output port is relatively negligible compared to the other delays, so that the demultiplexer does not generate delays.

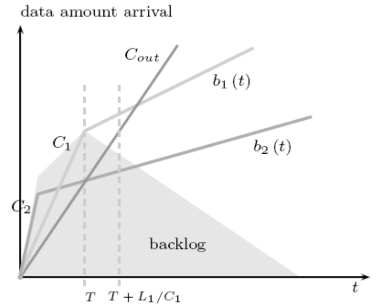

Fig. 2. Arrival and service curves and backlog evolution inside the two-input FIFO multiplexer.

2.2 Maximum end-to-end delays for crossing a switched Ethernet network

The computation of the upper bound end-to-end delays requires that special attention is paid to the input parameters of the previous equations. Indeed, the maximum delay value $\overline{D}$ depends on the leaky bucket parameters: the maximum amount of traffic σ that can arrive in a burst and the upper bound of the average rate of the traffic flow ρ. In order to calculate the maximum delay over the network, it is hence necessary that the envelope (σ, ρ) is known at every point in the network. However, as shown in Figure 3, only the initial arrival curve values (σ^0, ρ^0) are usually known, and the values for other arrival curves have to be determined. To calculate all the arrival curve values the following equations can be used:

$$\begin{aligned} \sigma_{out} &= \sigma_{in} + \rho_{in} D \\ \rho_{out} &= \rho_{in} \end{aligned} \tag{8}$$

For example, for the arrival curve (σ^1, ρ^1) in Figure 3 the envelope after the first switch is:

$$(\sigma^1, \rho^1) = (\sigma^0 + \rho^0 \overline{D_{switch}}, \rho^0) \tag{9}$$

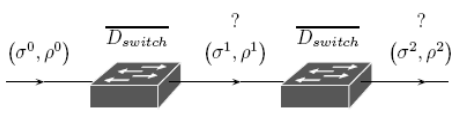

Fig. 3. Burstiness along a switched Ethernet network.

The last part of the method used to obtain the upper-bounded delay estimate is the resolution of the burstiness characteristic of each flow at each point of the network. First, the burstiness values are determined by solving the equation system:

$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & & & \vdots \\ a_{n2} & a_{n2} & \dots & a_{nn} \end{bmatrix} \cdot \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \vdots \\ \sigma_n \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix} \tag{10}$$

and after solving the above equation, the upper bound end-to-end delays are obtained from

$$\overline{D_i} = \frac{\sigma_i^h - \sigma_i^o}{\rho_i} \tag{11}$$

where h is the number of crossed switches.

3. COMPENSATING THE ESTIMATED TRANSMISSION NETWORK DELAY EFFECT WITH THE ROBUST CONTROL BASED APPROACH

In this chapter the information available about the dynamic behaviour of the network, the upper bound delay estimate, is integrated in the control law. The main idea behind the approach is first to represent the communication network induced delays in the frequency domain as an uncertainty around the nominal plant. Information about the upper bound delay is utilized in formulating the representation of the uncertainty. Next, robust control methods are used to generate a control law that is able to meet the design specifications, to maintain the system performance, and to make the system insensitive even in the worst case disturbance for all the plants in the uncertainty set. The “worst-case” uncertainty is assumed to occur when the network delay equals the theoretical upper bound delay estimated by the algorithm based on network calculus theory. In order to facilitate understanding, the synthesis of both is done in continuous time. For implementation the obtained controllers should be discretized.

3.1 Problem formulation

The problem is studied from the controller point of view as a control problem in which the properties of the communication network have to be taken into account in the controller design. For the controller, the system that is actually being controlled, the system G_P, is a combination of the nominal plant (assumed to be fixed and certain) and uncertain (unknown, but bounded) dynamical effects of the network E. With the weighting functions, w_I, and normalized perturbations, Δ, the following expression for the networked controlled plant G_P is obtained:

$$G_p(s) = G(s)(1 + w_I(s)\Delta(s)); \underbrace{|\Delta_I(jw)| \le 1 \forall}_{\|\Delta_I\|_\infty \le 1} \quad (12)$$

3.2 Representing the network induced delay.

Next, information about the upper bound delay of the network is utilized in creating the weighting functions w_I. The weight can be obtained by finding the smallest radius $l_I(w)$ that includes all possible plants:

$$l_I(w) = \max_{G_P \in \Pi} \left| \frac{e^{UBD_1 s} G(jw) e^{UBD_2 s} - G(jw)}{G(jw)} \right| = \max_{G_P \in \Pi} \left| e^{UBD_1 s} e^{UBD_2 s} - 1 \right|$$

$$l_I(w) = \begin{cases} \left| e^{(UBD_1 + UBD_2)s} - 1 \right|; w < \pi / (UBD_1 + UBD_2) \\ 2; w > \pi / (UBD_1 + UBD_2) \end{cases} \quad (13)$$

And choosing the weight w_I such that

$$|w_I(jw)| \ge l_I(jw); \forall w \quad (14)$$

For example in this case the following weight can be chosen:

$$w_I(s) = \frac{(UBD_1 + UBD_2) \cdot s}{1 + (UBD_1 + UBD_2) \cdot s / 3.465} \quad (15)$$

This delay estimate was originally proposed by Wang, et al., (1994) to represent uncertain delays in the H_∞ framework in the design of robust controllers.

3.3 Controller synthesis

For a SISO case the controller synthesis problem can be solved in a relatively straightforward manner, since the SISO case with one complex multiplicative perturbation the Robust Performance (RP) problem can be approximated as a weighted mixed sensitivity problem where the condition is slightly strengthened:

$$\left\| \begin{matrix} w_P S \\ w_I T \end{matrix} \right\|_\infty = \max_\omega \sqrt{|w_P S|^2 + |w_I T|^2} < \frac{1}{\sqrt{2}} \quad (16)$$

Where w_P is a weight for the sensitivity function S (usually an approximator of an integrator), and T is the complementary sensitivity function. For a MIMO case the use of a more complicated technique such as μ synthesis is required.

4. SIMULATION RESULTS AND DISCUSSIONS

In the simulations, the network of a real time process, a controller, and two overload traffic stations connected over a full duplex Ethernet switch, were used. The structure of the system is shown in Figure 4. To calculate the upper bound delay, the initial leaky bucket values of each stream were first identified. 6 are messages sent periodically. The traffic sent from the process to the controller is given by $b_1^0(t)$, and the traffic from the controller to the process by $b_2^0(t)$. The upper-bounds for these traffics will be computed in order to obtain the upper bounds, UBD_1 and UBD_2. We consider also background traffic ($b_3^0(t)$, $b_4^0(t)$, $b_5^0(t)$, $b_6^0(t)$) from the stations to the process and to the controller in order to overload the network:

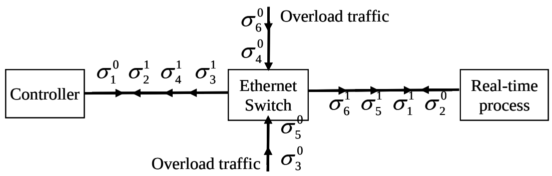

Fig. 4. The structure of the network

$$\begin{aligned} &b_1^0(t) = b_2^0(t) = \sigma_1^0 + \rho_1 t = 72 + 7200t \\ &b_3^0 = b_4^0(t) = b_5^0(t) = b_6^0(t) = \sigma_3^0 + \rho_3 t = 1526 + 305200t \end{aligned} \quad (17)$$

Next, the route of each stream was identified and the output burstiness equations were formulated. After solving the burstiness values the end-to-end upper bound delay for streams 1 and 2 are:

$$UBD_1 = UBD_2 = \frac{\sigma_1^2 - \sigma_1^0}{\rho_1} \approx 3.5\,ms \quad (18)$$

In evaluating the effects of the network on the control system performance, the following model of a real time process and a nominal controller were used (time in *ms*):

$$P(s) = \frac{2}{(s+5)(s+0.2)} \quad C(s) = \frac{K_P s + K_I}{s}, \quad K_P = 0.5508, \quad K_I = 0.4529 \quad (19)$$

The delay compensation strategy based on the robust control approach was implemented by solving the mixed sensitivity problem in Equation 16. Equation 15 was used as a weighting function for the complementary sensitivity function *T*. As a weighting function w_P for the sensitivity function *S* the following approximation of the integrator was implemented:

$$w_P(s) = \frac{s/M + \omega_B}{s + \omega_B A} \quad (20)$$

Where ω_B is the bandwidth where control is effective, M is the desired maximum peak of wb, and A is a small number used to avoid numerical problems. The H_∞ optimal controller for this mixed sensitivity problem was found using the Matlab™ Robust control toolbox.

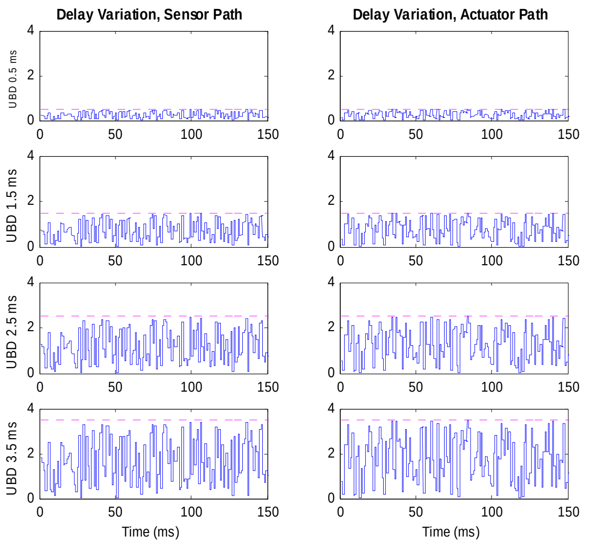

Fig. 5. Evolution of the sensor and actuator network delays.

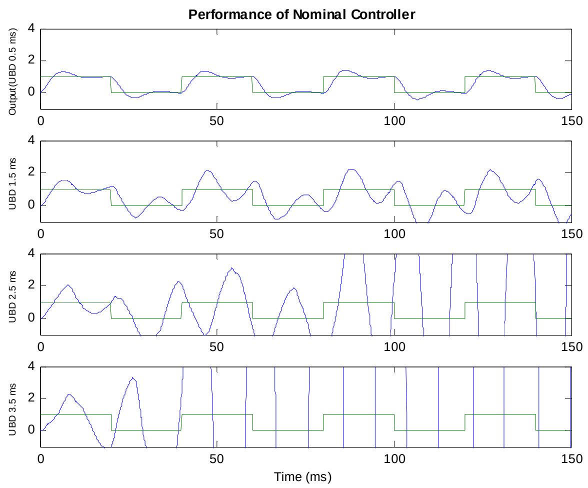

Fig. 6. Performance of the nominal controller as the delay increases

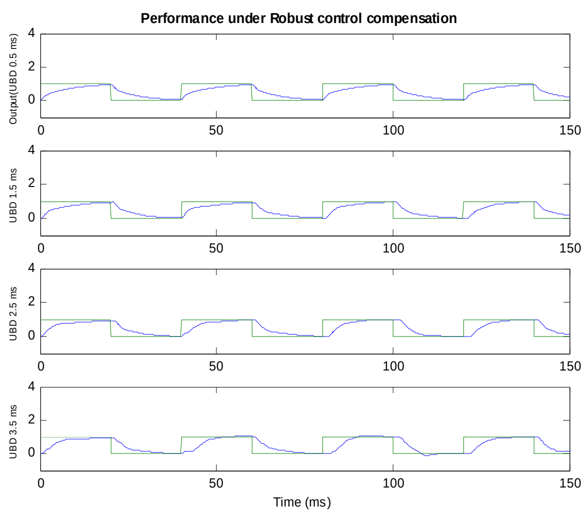

Fig. 7. Performance of the robust controller as the delay increases.

The simulation results are presented in Figures 5-7. Figure 5 shows the evolution of the sensor and actuator network delays, Figure 6 represents the performance of the system when controlled with a the nominal controller (Equation 19) as the delay increases, and Figure 7 indicates the performance of the robust controller as the delay increases. From the figures it can be concluded that the nominal system becomes unstable when the delay increases. The stability of the feedback control loop is regained when a delay compensation strategy such as the robust control based approach is implemented.

5. CONCLUSIONS

In this paper an analysis of the networked control system has been presented. A procedure for obtaining the upper bound delay value in the switched Ethernet network was presented, and the obtained delay estimate was used in the control compensation. Two control compensation strategies, the Smith predictor based compensation strategy and the robust control based compensation strategy, were presented and compared. It can be concluded that the upper bound delay estimate is an important measure of the networked control system which can also be used for the design and synthesis of a control system.

ACKNOWLEDGEMENTS

This research has been conducted as a part of the Networked Control Systems Tolerant to Faults (NeCST) project IST-004303 that is partially funded by the EU. The authors gratefully acknowledge the support.

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A MODELING AND OPTIMIZATION TOOL FOR THE EXPANDABLE POLYSTYRENE BATCH PROCESS

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Abstract

The Expandable Polystyrene (EPS), material of the insulation productions and packages, is commonly produced in a batch process. In this paper we demonstrate the optimization and modeling application for the EPS-batch process. The application consists of a production optimization tool and a simulation tool for the process parameters based on the Multi-Layer Perceptron network (MLP) with retrain properties. The software can be used at the operational level as well as at the process management level. The features are programmed into standalone software built up in the Matlab environment.

Keywords: batch process, modeling, simulation, process optimization, Multi-Layer Perceptron (MLP).

1 Introduction

A batch process is commonly used for producing Expandable PolyStyrene (EPS). Batch processes are typically based on predefined process recipes. In practice, the EPS polymerisation reaction in the batch reactor is a very sensitive process and is affected by numerous variables, which makes the process difficult to control. Moreover, EPS production has to be able to satisfy the aims and quality requirements of the markets, which causes additional demands on process control. Thus, there is clearly room for intelligent mathematical methods and computational modeling systems such as artificial neural networks (ANN) in the control of the EPS process and optimization of the production.

The selling EPS production is divided into fractions of the bead size. For example, the bead size for the insulation product is different from the bead size for the cup. Each of the batches produces the load of beads, where the mean bead size is controlled, but the shape of the bead size distribution is typically Gaussian. Therefore, the production of the campaign is a sum of the Gaussian bead size distributions. Thus, the biggest challenge is to produce the optimal bead size fractions for the markets.

Several studies have demonstrated that ANN can provide an efficient method for modeling industrial data [1-9]. One of the most popular ANN methods, the Multi-Layer Perceptron network (MLP) [1-3, 6] has been successfully applied in many areas of research and for process optimization. Previous study [6] demonstrated the efficiency of the MLP for EPS batch process. However, there are not many real applications based on ANN methods in industrial use.

In this paper we demonstrate the optimization and modeling application for the EPS-batch process. The application consists of a production optimization tool and a simulation tool for the process parameters based on the Multi-Layer Perceptron network. The optimization and the modeling features are programmed into standalone software built up in the Matlab environment. The software is tailored for the needs of the EPS production company StyroChem Ltd.

2 Methods

2.1 The EPS batch process

The studied process was a typical suspension polymerisation batch process, which is commonly used for producing EPS (Expandable PolyStyrene). The reactor has a powerful mixer and the cooling system in the inner wall. The main raw materials are styrene, water, pentane, stabilisation agents and additives. The general structure of the EPS reactor is illustrated in Figure 1.

The duration of each batch takes about 12 hours. At first, the main chemicals are added into the reactor and the process is heated up to the polymerisation temperature. The polymerisation stage is executed in a pressure-temperature range below the boiling point of the styrene-water suspension system. After the polymerisation stage the process continues into the impregnation stage, where the blowing agent (pentane) is impregnated into the beads. The impregnation stage assumed to be negligible in the means of bead size distribution. The final stages are cooling and sieving. The end product is a load of solid EPS beads.

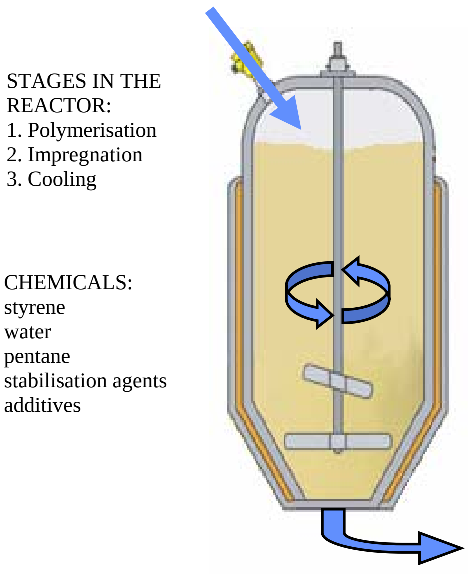

Figure 1. The polymerisation batch process.

It is common knowledge that the basic variables in the term of the bead size are the mixing properties and the amount and quality of the suspension stabilizers. However, suspension polymerisation of styrene is a very sensitive process and numerous variables affect it. Some of these variables cannot be measured or followed by in a reasonable way. For example, analyzing all impurities from all raw materials is too heavy a task for any industrial laboratory. Some variables are quite easily measurable, but have not been traced due to the assumption that they would not have a significant contribution to the process. To be able to model the process the studied system required elimination of the variables, which were assumed to be inessential.

The shape of the bead size distribution of each batch is almost Gaussian. The mean bead size can be controlled by a dosage of chemicals and mixing conditions, but the bead size distributions are normally Gaussian.

2.2 The process data

The process data can be divided into three groups: recipes, results and process parameters. The recipes, such as the amount of stabilisation agents, are specified individually for each batch. The most important information, concerning the end product, is the bead size distribution. The bead size distribution is specified in a laboratory by laboratory sieves. The recipes and the measurements made in a laboratory are archived into Microsoft Excel™.

2.3 The Multi-Layer Perceptron

Multi-Layer Perceptron (MLP) is widely used network model. The MLP model is very general and can, in theory, represent almost anything. It consists of one input layer, hidden layers (typically one or two), and an output layer. The input signals are processed through successive layers of neurons in a forward direction on a layer-by-layer basis. The input layer simply feed directly the corresponding values from the input pattern into the first hidden layer. Each neuron of a hidden layer and an output layer computes a linear combination of the outputs of the neurons of the previous layer. The coefficients of the linear combinations (plus biases) are called the weights.

Supervised networks, such as MLP networks, must be trained to a given problem. The most popular training techniques are a backpropagation algorithm. It compares the output values with the correct answer to compute the value of some predefined error-function. The training, an iterative process, determines a set of weights, which minimizes the error between the actual and expected outputs for all input patterns.

3 The application

The application is coded in Matlab software platform (Mathworks, Natick, MA, USA), and compiled for the stand-alone software by the Matlab compiler. The purposes of the application are optimization of the production, and simulation of the process parameters. In addition, the software has versatile visualization properties for viewing data.

The software consists of 3 graphical interfaces: the production optimization interface, the training interface for the MLP model, and the simulation interface. These interfaces are shown in Figures 2 - 4.

3.1 Optimization of the production

The main idea of the optimization is to define the optimal feasible production for the marketing demands. The marketing demands are compared to the historical data of bead size distributions of the batches. Before the comparing, the data are fitted in a function of a mean bead size (D_{50}) by Least Mean Square (LMS) method.

The distribution of the bead size in the production campaign is a sum of Gaussian distributions. The aim of the optimization of production is to predefine the optimal mean bead size for one or two Gaussian distribution, which satisfy the marketing demands and minimize the amount of production. The marketing demands are predefined in tons or in percentage for different fractions. The optimization chain can be described as follow:

1. Set the fractions (the products to sell) of the bead size
2. Set amount of production (in tons or in percentage) of the fractions to be produced
3. Set the campaign recipe (type of EPS)
4. LMS for the fractions
5. Define the optimal feasible production by use of one or two distributions

The distribution of bead size is divided for fractions to be sold. This prospective information is utilized for planning the production and marketing of EPS. In addition, the fraction parameters defined in the optimization window can be used in the modeling phase for simulate the process parameters. The simulation supports the optimization purpose.

3.2 Training the MLP model

The data rows for the training phase are selected in an optimization interface (shown in Figure 2). For example, it is useful to cut the outliers, because they could disturb the accuracy of the model. In a training interface (shown in Figure 3), the user can set the inputs and outputs variables for the model from the menu bar. In addition, there is a possibility to add new input variables by calculating averages of the previous rows of variables. Some basic parameters for the training of the MLP model such as a number of the hidden neurons, a training algorithm, the training rows, and the validation rows can be set in the interface. A complete setup of the parameters, concerning the MLP model, is assembled in a separate text file.

Validation of the MLP model can be done by scatter plots, the root mean square errors, the index of agreement, and the correlation coefficient. Finally, the model is saved for the simulation purpose.

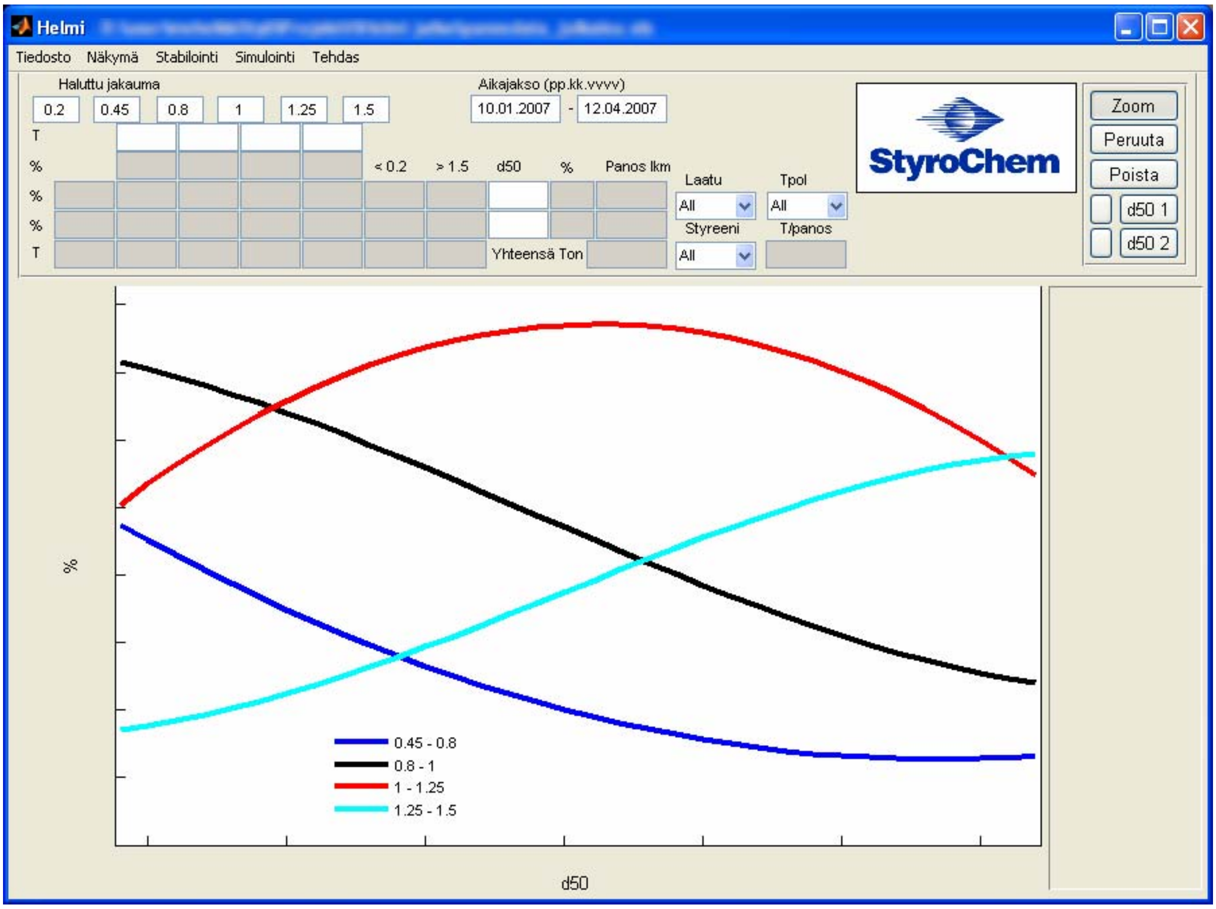

Figure 2. The graphical interface of the production optimizing tool. The mean square errors (curves) are fitted into the historical data (small dots). The dashed lines show two optimal distributions of the bead size to satisfy the production tons (T) based on information of the markets.

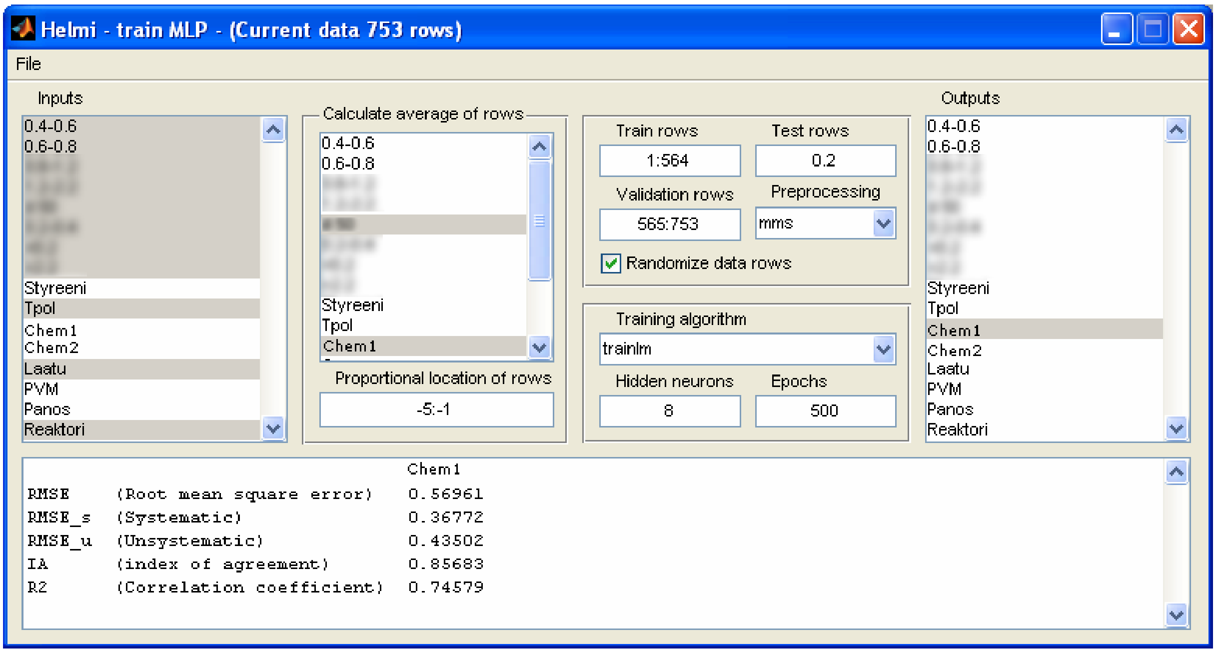

Figure 3. The graphical interface for training of the MLP-model. The inputs and outputs variables can be selected from the menu bars. In addition, the user can set some of the basic training parameters such as the training algorithm and the number of hidden neurons.

3.3 Simulation

In the simulation interface (shown in Figure 4) the user can simulate the MLP model. The output, such as the dosage of the chemical X, will appear until all the inputs are set. The inputs are filled in automatically, if values of the inputs are defined in the process optimization interface. Thus, the calculations made in the optimization interface can be used for inputs in the MLP modeling phase.

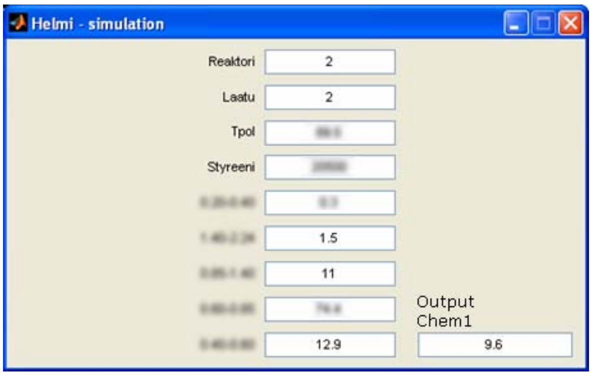

Figure 4. An example MLP simulation in the simulation interface. The inputs are in the middle of the simulation interface and the output is on the lower right corner of the window.

4 Discussion

The main purpose of the study was to integrate process management with process control into functional software. The results of the study show that the application is an efficient tool for optimization of a batch process and modeling process parameters. A prerequisite for the efficient use of the application are user-friendly graphical interfaces with versatile visualization properties. The software can be used at the operational level as well as at the process management level. In addition, the software is generic because the data is updated automatically from the databases, and the MLP model can be retrained quickly.

EPS production of a batch process based on predefined recipes achieves the required bead size distribution, which is nearly Gaussian. The production can follow the requirements of the market easily by using more than one recipe at the same time. The application can calculate the optimal production by combining the distributions. These calculations can be used as inputs in the MLP-modeling phase where process parameters such as chemical dosages are estimated. The marketing can set amount of the production (tons) for each fraction, and the software defines the optimal process parameters. Thus, production will economize on process and storage costs. That was proved in a test use of the software in company StyroChem.

5 Conclusion

The present application integrates production optimization and process modeling. The results indicate the MLP analysis with functional data preprocessing tool provides an efficient method for data analysis in the process industry. Therefore, this kind of intelligent data-driven approach is a fruitful way of developing tools for the batch process optimization.

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7 Acknowledgement

This research was supported by StyroChem Ltd..

GAIN SCHEDULING CONTROL IN SECONDARY AIR CONTROL SYSTEM

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Abstract: Gain scheduling control in secondary air control is developed and tested by simulating. The real secondary air control system includes four PI controllers without any compensation of interactions, and the created system emulates it. A secondary model based on the Hammerstein structure is utilized in the tuning of the controllers. The parameters of the model are grounded on process experiments in a full-size bubbling fluidized bed boiler. B-spline basis functions are used to guide the parameters of the controllers. The results suggest that gain scheduling enables the better performance of of the controllers. The use of parameter calculation methods requires however careful consideration due to the interactions of the system.

Keywords: PID control, process control, air pollution, environmental engineering, fluidized bed boiler, power plant.

1. INTRODUCTION

There is a large interest in combustion of multi-fuels in Finland. Multi-fuels are usually understood as mixtures of different bio-fuels, which have a significant role in the reduction of CO_2 emissions. In some case coal and oil are burned with bio-fuels. However, the combustion of those kinds of fuels or fuel-mixtures has different properties compared to the fossil fuels (coal, gas, and oil). Bio-fuels are very inhomogeneous. The properties (heat value, moisture content, homogeneity, density, mixability) may vary in a large range. The disturbances in fuel feed are not predictable or directly measurable, only their effects on the combustion, on the flue-gas emission, on the steam generation and on the power production can be observed; e.g. through flue-gas oxygen-content or through the variation of steam pressure, respectively.

In the fluidized bed boiler, the hot sand bed dries and mills the fed fuel before burning in order to smooth the combustion process. The primary air is blown from the bottom of the boiler to fluidize the bed and the secondary airs are blasted above the bed. The secondary air flows are often staged in two or three levels to improve the control of the combustion process.

The amount of excess air can be measured through flue-gas oxygen-content controlled by changing the flow of secondary air. The amount of excess air affect NO_x and CO emissions, and therefore the improvement of the current secondary air control system is necessary.

2. PROCESS

The studied secondary air process contains three air feeding levels (Leppäkoski *et al*, 2004), (Leppäkoski, 2006). The air flow in each air level is independently controlled by the air damper. The secondary air pressure is controlled by changing the speed of the air fan blower. The lowest air feeding level is just above the fluidized bed; the middle level is little above the lowest level; and the upper level is at the top of the boiler. All changes in the air pressure control signal and air flow control signals affect on the air pressure and the air flows. Note that the structure of the secondary air systems varies since the process is man-made and the structures might be modified.

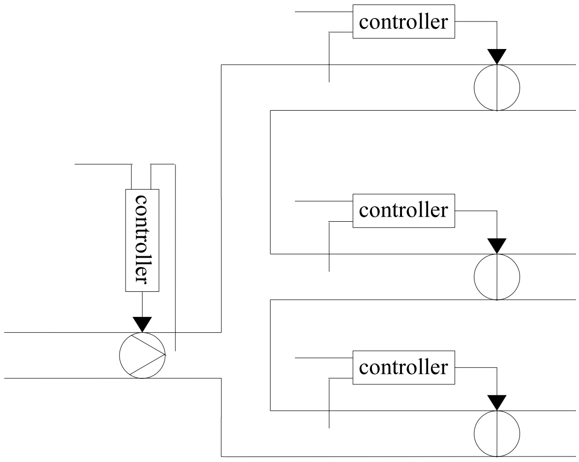

Fig. 1. Structure of the secondary air control system

The secondary air process control system has two purposes: a) to be a part of ratio control between the fuel flow and air flow, and b) to be a part of flue-gas oxygen-content control. The power controller or the main controller sends a signal to a calculation block, which defines the reference values to the controllers of the secondary air system and the primary air system. Timing between the fuel feeding and air feeding is essential in order to continuously maintain the correct air/fuel ratio without disturbing flue-gas oxygen-content. The fuel/air ratio control is likely performed in the best way by using the parallel fuel/air ratio control, and the relation is tried to maintain in a defined value. In flue-gas oxygen-content control, the secondary air flow controllers track the changes influenced by the flue-gas oxygen-content controller. They form a cascade loop, in which the flue-gas oxygen-content controller is the outer controller and the secondary air flow controllers are in the inner control loop.

3. MODEL FOR CONTROL DESIGN

The secondary air system may be modelled by using a block-oriented structure as, for instance, the Hammerstein structure. The structure contains a non-linear static part followed with a linear dynamic part (Ikonen and Najim, 2002). Generally, the Wiener/Hammerstein structures may suit well in modelling chemical processes (Ikonen and Najim, 2001). In this case, the static part consists of the tensor product, and it can be considered as a grey-box model made for this specific process to improve transparency and include the constraints of the process (Leppäkoski *et al*, 2004), (Leppäkoski 2006). The linear part is a transfer function with unit gain.

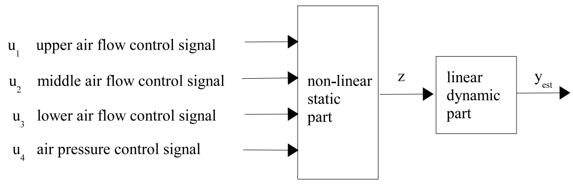

Fig. 2. Structure of the secondary air model.

The secondary air process is described by using the Hammerstein structure. The structure contains a non-linear static part which follows a linear dynamic part (Fig. 2). The output error model was applied in the dynamic part. Various models can be utilized in the static part. In this case, the static tensor product calculation part can be understood as the grey-box model created for this specific process, in order to improve transparency and include the constraints of the process. The input and output values were scaled to match unit interval before training. The non-linear model is iteratively calculated by applying the Levenberg-Marquardt method. The static part is first estimated, and then the linear part is estimated by utilizing the latest static model. The procedure is continued until the improvements of the model are below a determined limit. In validation, residual analysis was employed by plotting histograms and residuals versus time diagrams.

The aggregate MIMO model has four inputs and four outputs., and it contains four MISO models. Three air damper control signals and an air blower control signal are the inputs; three air flow measurements and an air pressure measurement are used as the outputs. The inputs and outputs are numbered from one to four, from the upper air flow to air pressure.

4. TUNING

The purpose is to imitate a real secondary air system including the control system. Four PI controllers without interaction compensation are used. The performance of the real system is, at most, satisfactory, and therefore the control should be improved.

Different solutions can be used to compensate non-linearity in the process (Isermann *et al*, 1992). Gain scheduling, the use of inverse model and the continuous adaptation of control are possible approaches. In order to ensure equal operation over whole region, gain scheduling is a reasonable solution. Gain scheduling may offers a method, which can be modified on site.

The guidance of the controllers may be conducted by employing various methods. The methods based on local learning may be considered to be suitable to guide the controllers of the secondary air system. B-spline basis functions may be used in the B-spline neural network or in the ASMOD model (Brown and Harris, 1994), (Kavli, 1993). Even the use of only main control signal of each secondary air process controller in gain scheduling improves significantly the performance when comparing to the controller with fixed parameters.

Different criteria may be used in tuning the controllers. The ISE (the integral of square error) criterion, the IAE (the integral of absolute error) criterion, the ITAE (the integral of time and absolute error) criterion and the infinitum norm criterion are quite well-known (Åström and Hägglund, 1995), (Brown and Harris, 1994), (Shinskey, 1994). The ISE, IAE and ITAE criteria are studied. The ISE criterion expresses the largest oscillation in the performance of the controllers, and the ITAE criterion shows the smallest oscillation in the performance of the controllers. The ITAE criterion punishes for long oscillation time. The IAE criterion is between ealier mentioned criteria. The controllers of the secondary air system are tuned by applying the ITAE criterion.

The control system is trimmed in two phases. Firstly, the system is considered as four SISO loops. Secondly, the system is investigated as a MIMO case. The Levenberg-Marquardt method is employed in the calculations, see for instance (Ikonen and Najim 2002).

In the first phase, the values of the gain (Kc) and the integral time (Ti) are separately computed for each controller without consideration of any interaction (SISO cases). The secondary air model is linearized in defined load levels (step 10%, 20% – 90%), and the linearized results are utilized in tuning. In each level, the set points to the secondary air system controllers are determined by applying a pre-defined calculation to maintain the correct air/fuel ratio as in the full-size power plant. The results are calculated by employing the changes in the set points.

In the second phase, the secondary air model is utilized in the tuning of the control system. The values from the first phase are used as initial values. Other three controllers function when each controller is tuned (MIMO cases). The same load levels are employed as in the first phase. Few iterations may be required.

The computed parameters of the controllers from MIMO cases are fitted to linear B-spline basis functions. The parameters of the gain and integral time are guided by eight basis functios. The control signals are selected to be the scheduling variables when the basis functions of each controller are managed by the control signal of each controller.

In the Tables 1 and 2, the results from these two tuning phases are compared. The differences are computed by applying the equations 1 and 2. In order to maintain the stability of the system, the all values of the gain and integral time in the MIMO cases are decreased and lengthened in the level 80% and 90% by using the numbers 0.9 and 0.55. The numbers in the Tables are affected by these numbers.

$$Kc(differ.) = \frac{(Kc(MIMO) - Kc(SISO))}{Kc(SISO)} \cdot 100\% \quad (1)$$

$$Ti(differ.) = \frac{(Ti(MIMO) - Ti(SISO))}{Ti(SISO)} \cdot 100\% \quad (2)$$

According to the results from Tables 1 and 2, the differences remain moderate until the load levels 80% and 90% is reached. The controller 1 (the upper air flow) do not function between the level 20% and 50% as in the real case. The values of the gain seem to change slightly more than the values of the integral time before the level 80%. The effect of interactions cause probably the decline of the gain. Especially in the level 90%, tuning is highly difficult. The interactions begin likely violently to disturb the tuning of the controllers. Furthermore, the used optimization method does not probably find the global optimum point but it sticks a local optimum point. Other optimization method may be more suitable although it can be computionally much more expensive.

Table 1. Kc(difference) (MIMO)/(SISO) (%).

	Contr. 1	Contr. 2	Contr. 3	Contr. 4
Level 20%	(0)	- 17.9	- 14.7	- 7.42
Level 30%	(0)	- 20.2	- 7.13	- 0.215
Level 40%	(0)	- 17.3	- 0.892	12.5
Level 50%	(0)	- 12.2	7.21	26.7
Level 60%	- 18.1	- 2.93	14.6	26.7
Level 70%	- 4.60	- 0.016	18.5	5.48
Level 80%	- 23.2	- 13.8	- 12.9	1.61
Level 90%	- 68.7	- 45.9	- 45.0	- 10.2

Table 2. Ti(difference) (MIMO)/ (SISO) (%).

	Contr. 1	Contr. 2	Contr. 3	Contr. 4
Level 20%	(0)	- 4.12	- 3.30	- 0.289
Level 30%	(0)	- 5.37	- 0.841	2.83
Level 40%	(0)	- 3.58	0.169	8.85
Level 50%	(0)	- 2.24	4.61	12.9
Level 60%	- 3.02	1.04	5.86	17.5
Level 70%	- 3.86	2.18	4.44	5.45
Level 80%	7.77	13.9	105	- 16.1
Level 90 %	326	118	92.7	38.8

In Figs 3 and 4, the use of gain scheduling control is presented. The load is gradually changed from the the level 20% to 90%, and the set points are continuously tracked by the controllers of the secondary air control system. The set points are properly followed. The rapid action of the controllers is revealed by a large change in the set point of controller 3. In reality, similar movements after the point 200 as shown Figs 3 and 4 are not possible. The behaviour of the controllers in the level 90% is better when the fixed parameters used in the level 60% are applied. The inputs and outputs are smoother. The tuning criterion must be expanded by a constraint. The overshooting of inputs should be prevented.

In Figs 3 and 4, the use of the fixed parameters used in the level 20% is presented. The load and the set points are similarly changed. After a large change in the set point of the controller 3, the controller 1 begin to oscillate disturbing other controllers. This discovers the complexity of the control system.

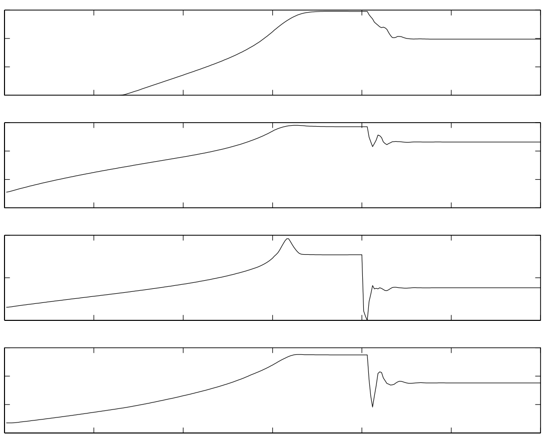

Fig. 3. Control inputs when the set points are tracked from the load level 20% to 90% by applying gain scheduling control, and then a large change in the set point of controller 3.

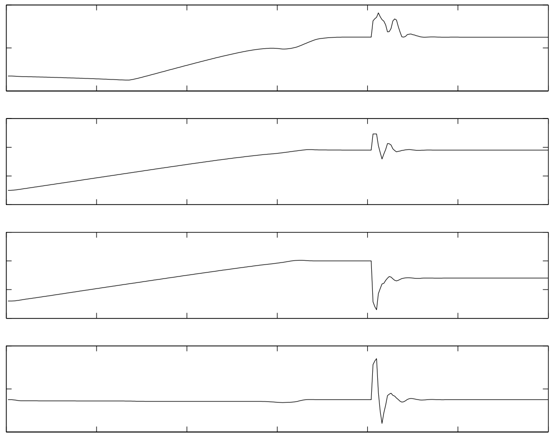

Fig. 4. Simulated outputs when the set points are tracked from the load level 20% to 90% by applying gain scheduling control, and then a large change in the set point of controller 3.

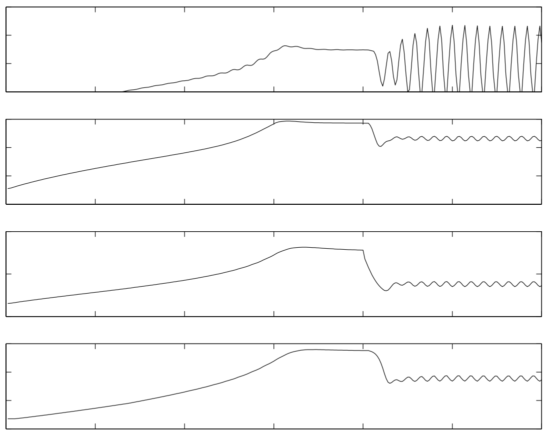

Fig. 5. Control inputs when the set points are tracked from the load level 20% to 90% by applying fixed parameter control, and then a large change in the set point of controller 3.

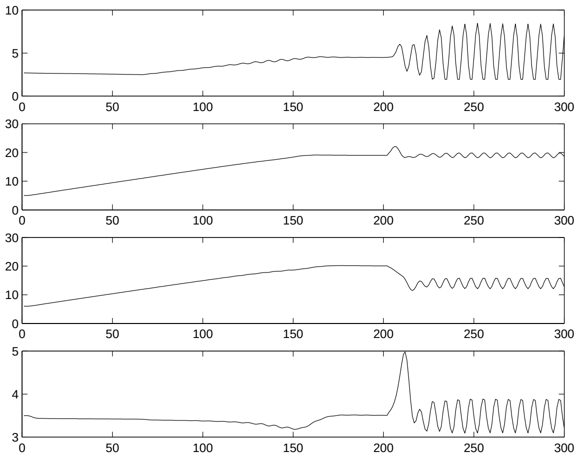

Fig. 6. .Simulated outputs when the set points are tracked from the load level 20% to 90% by applying fixed parameter control, and then a large change in the set point of controller 3.

5. CONCLUSIONS

The controllers can be tuned in a suitable way when the process models are realistic enough. The objective is to find the methods, which can be applied in practise. Local optimum points may disturb the searching of optimal control parameters. Gain scheduling may guarantee better and smoother performance over the whole operation region. A drawback is laborious tuning. Further computerized control design decreases likely the burden of tuning. Moreover, fault tolerant control may be necessary to apply in the control system due to the possibility of malfunction of the air dampers. The better tracking of the set points in the secondary air control system enables also the better tuning of the flue-gas oxygen-content contol system.

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VOLTERRA MODEL BASED PREDICTIVE CONTROL, APPLICATION TO A PEM FUEL CELL.

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Abstract: This paper presents a non linear model predictive controller for a PEM fuel cell for which the starvation control is the main objective. A second order Volterra model for control is obtained using input/output data for which the power supplied by the fuel cell is considered as a measurable disturbance. The controller developed allows to solve the nonlinear objective function in a way that it can be actually implemented in fast systems like Fuel cells. The use of a nonlinear controller is justified while comparing the outcome obtained with a linear controller of the same class.

Keywords: Model Identification, Model predictive control, Fuel Cells.

1. INTRODUCTION

Fuel cells technology has proven a great development in recent years, mainly in the search of efficient and less polluting alternative sources of energy to the traditional ones. There are still many open issues regarding the practical use of this technology, depending on the type of fuel cell being considered. These research topics range from manufacturing issues to materials science, and process control is among those areas of active work (Prukushpan *et al.*, 2004*b*), (Prukushpan *et al.*, 2004*a*). In this paper, a Polymer Electrolyte Membrane (PEM) fuel cell is considered, whose fast dynamical response and low temperature operation makes it suitable for mobile applications.

Linear controller design techniques are widely employed in industry, although a great deal of processes are non-linear. In many situations the process is operating in the vicinity of a nominal operating point and therefore a linear model can provide good performance. The simplicity and the existence of tested identification techniques for linear models allows an easy and successful implementation of linear controllers in many situations. However, there exist many situations in which non-linear effects justify the need of non-linear models, such as in the case of strong non-linear processes subject to big disturbances or setpoint tracking problems where the operating point is continually changing, showing the non-linear process dynamics.

When the model is nonlinear the resulting control schemes present some challenging problems. A clear example is Linear Model Predictive Control, (MPC) which is arguably the most popular advanced control technique in industry, due to the intuitive control problem formulation and its ability to deal with economic objectives and operating constraints (Camacho and Bordons, 2004). However, its nonlinear formulation has a lot of open issues, and its scarce influence on industrial control practice is nowadays due to two main reasons: on one hand its online computational complexity and on the other, its inability to construct a nonlinear model on a reliable and consistent basis (Lee, 2000), despite nonlinear dynamics are significant in industrial processes.

Using a nonlinear model changes the predictive control problem from a convex quadratic program to a non-convex nonlinear problem, which is much more difficult to solve. Furthermore, in this situation there is no guarantee that the global optimum can be found, especially in real time control, when the optimum has to be obtained in a prescribed time. The solution of this problem requires the consideration (and at least a partial solution) of a nonconvex, nonlinear problem (NLP), which gives rise to a lot computational difficulties related to the expense and reliability of solving the NLP on line. Nevertheless, when the process is described by a Volterra model, efficient solutions for the model predictive control problem can be found. This solution makes use of the particular structure of the model, giving an on-line feasible solution.

The main advantage about the use of Volterra models relies in the fact that being a natural extension of the linear convolution models, they are quite straight forward to obtain from input/output data without any prior consideration about the process model structure. Hence, in this paper the ability to capture non linear dynamics of the process combined with the explicit consideration of operation constraints are taken into account.

The paper is organized as follows. First the PEM fuel cell is described, as well as the control objective. In the following section, the model prediction equations and the optimization procedure that involves the controller is presented. Then the proposed control strategy is tested under simulation of a PEM fuel cell model, where a comparison with other control techniques is performed. Finally, the major conclusions are drawn.

2. PEM FUEL CELL

Polymer Electrolyte Membrane (PEM) Fuel Cells is one group of fuel cells that run at low temperature and show fast dynamical response, making them suitable for mobile applications. As in all fuel cells there are many components making up the whole power system in order to be able to supply electrical power. Typical components include DC/DC or DC/AC converters, batteries and in the case the fuel cell is not fed directly with hydrogen, a reformer must also be used. Therefore, there are many control loops schemes depending on the devices that must be controlled. The lower control level takes care of the main control loops inside the fuel cell, which are basically fuel/air feeding, humidity, pressure and temperature.

The work carried out in this paper deals with the low level control of the fuel cell, where several techniques exist to fulfil one of three main possible objectives to achieve: maximum efficiency, voltage control or starvation prevention. In all cases, the controller manipulates air and fuel feeding, playing with compressor voltage and hydrogen supply valve.

The controller developed will consider that the operating temperature inside the cells and reactive humidity are controlled, so these variables can be considered to be constant. Hydrogen supply is controlled using the inlet valve in such a way that hydrogen pressure in the anode tracks oxygen pressure in the cathode. This is done by a simple proportional controller in order to avoid high differential inlet pressure which could spoil the device. The main control action is therefore oxygen (or air) pressure, which is manipulated by acting on the compressor voltage.

The control criterion considered for the controller will be starvation. This is the worst phenomenon that can take place in a fuel cell, since once it has appeared the only way to deal with it is to switch the cell off or in other case the cell could be destroyed. Starvation is related to the amount of available oxygen inside the cell and takes place when this amount drops below a certain limit. Oxygen excess ratio is an indicative of the occurrence of this situation and can be considered a good performance index. It is defined as:

$$\lambda_{O_2} = \frac{W_{O_2,in}}{W_{O_2,react}} \tag{1}$$

Being $W_{O_2,in}$ the amount of oxygen that reaches the cathode and $W_{O_2,react}$ the amount of oxygen that really reacts. This variable must be supervised and kept above a threshold to maintain a safe operation regime.

The objective criterium must be achieved independently of the load demand, that is, the current that the cell must supply at each moment, which is the main disturbance. Therefore the process inputs are the compressor voltage which is the manipulated variable and the load current that is the disturbance. The main process outputs are oxygen excess ratio and cell voltage.

3. VOLTERRA MODEL BASED PREDICTIVE CONTROLLER

Volterra models are given, in their quadratic formulation, by equation (2). In which the additional second order terms in form of crossed products of former inputs are able to capture some nonlinear behavior of industrial processes. In table (1) the are explained the meaning for the parameters involved in the model.

$$y(k+d) = h_0 + \sum_{i=0}^{N_1} h_{1i} u(k-i) + \sum_{i=0}^{N_2} \sum_{j=i}^{N_2} h_{2ij} u(k-i) u(k-j) \quad (2)$$

Table 1. Volterra Model Structure

d	Delay
N_1	Linear Truncation Order
N_2	Quadratic truncation Order

Once the model has been defined it is possible to build the prediction equations, whose structure reminds of those of the linear MPC (Clarke *et al.*, 1987), except for new terms that appear due to the nonlinear extension:

$$\begin{aligned} y &= Gu + c + f \\ c &= Hu_{past} + p + g \end{aligned} \quad (3)$$

In equation (3) all the elements for the prediction are presented. The vector of predicted system outputs y depends both of past plant inputs c and future inputs that will be given during the control horizon. The vector of future control actions is u, which is the one that has to be calculated, and f is a vector containing all the quadratic terms of future control actions. This is the term giving the nonlinear characteristic to the optimization problem.

On the other hand, all the past history of the dynamic is contained in c whose dependence of past input / outputs of the system is explained trough the past control actions u_{past}, prediction error p, and the quadratic past inputs g.

Considering N_p and N_u as the prediction horizon and control horizon respectively, the matrices involved in equation (3) are:

$$\mathbf{G} = \begin{bmatrix} h_1(1) & 0 & \dots & 0 \\ h_1(2) & h_1(1) & & 0 \\ \vdots & \vdots & \ddots & h_1(1) \\ \vdots & \vdots & & h_1(1)+h_1(2) \\ \vdots & \vdots & & \vdots \\ h_1(p) & h_1(p-1) & \dots & \sum_{i=1}^{p+m-1} h_1(i) \end{bmatrix}$$

$$\mathbf{H} = \begin{bmatrix} h_1(2) & h_1(3) & \dots & h_1(N_1) & 0 \\ h_1(3) & \dots & h_1(N_1) & 0 & \vdots \\ \vdots & \vdots & 0 & \vdots & \\ h_1(N_1-1) & h_1(N_1) & \vdots & & \\ h_1(N_1) & 0 & & & \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The prediction error p is calculated as the difference between the measured value of the process output and predicted model output at each sample time, and it is considered constant for the rest of the prediction horizon.

The computation of the elements in vectors f and g is done through a proper partition of the quadratic terms. The rearrangement is as follows: The crossed future-future and future-past control action terms will be included in f. On the other hand g will account only for past-past input terms.

Defining a matrix B containing the second order coefficients as in (4), the calculation of the terms of f_i and g_i can be written as in (5) and (6) respectively. In order to illustrate this structure it has been chosen $N_2 = 4$

$$\mathbf{B} = \begin{bmatrix} h_2(1,1) & h_2(1,2) & h_2(1,3) & h_2(1,4) \\ 0 & h_2(2,2) & h_2(2,3) & h_2(2,4) \\ 0 & 0 & h_2(3,3) & h_2(3,4) \\ 0 & 0 & 0 & h_2(4,4) \end{bmatrix} \quad (4)$$

$$\begin{aligned} f_1 &= \left[u(k)\ 0\ 0\ 0\right] \mathbf{B} \\ &\quad \left[u(k)\ u(k-1)\ u(k-2)\ u(k-3)\right]^T \\ f_2 &= \left[u(k+1)\ u(k)\ 0\ 0\right] \mathbf{B} \\ &\quad \left[u(k+1)\ u(k)\ u(k-1)\ u(k-2)\right]^T \\ &\vdots \\ f_p &= \left[u(k+p-1)\ \dots\ u(k+p-4)\right] \\ &\quad \mathbf{B} \\ &\quad \left[u(k+p-1)\ \dots\ u(k+p-4)\right]^T \end{aligned} \quad (5)$$

$$\begin{aligned} g_1 &= \left[0\ u(k-1)\ u(k-2)\ u(k-3)\right] \\ &\quad \mathbf{B} \left[0\ u(k-1)\ u(k-2)\ u(k-3)\right]^T \\ g_2 &= \left[0\ 0\ u(k-1)\ u(k-2)\right] \\ &\quad \mathbf{B} \left[0\ 0\ u(k-1)\ u(k-2)\right]^T \\ &\vdots \\ g_p &= \left[0\ 0\ 0\ 0\right] \mathbf{B} \left[0\ 0\ 0\ 0\right]^T \end{aligned} \quad (6)$$

The control action is computed in order to minimize a quadratic function, that has been taken as shown in equation (7).

$$J = \sum_{j=N_{p1}}^{N_{p2}} [\hat{y}(t+j \mid t) - w(t+j)]^2 + \sum_{j=1}^{N_u} \lambda [\Delta u(t+j-1)]^2 \quad (7)$$

Following the ideas of Doyle et al. (Doyle *et al.*, 2002), an iterative algorithm is proposed to obtain an approach to the optimization problem that arises while dealing with VPC.

For the unconstrained case, the iterative algorithm is:

Step 1. set $i = 1$.

Step 2. Calculate c and u solving the least squares control problem in (8).

$$\begin{aligned} c &= Hu_{past} + g + p \\ u &= (G^t G)^{-1} G^t (s - c - f) \end{aligned} \tag{8}$$

Step 3. Determine if the condition to end the iteration process is met:

$$|u^i(k) - u^{i-1}(k)| \leq \Delta \tag{9}$$

where Δ is the desired tolerance.

- If the condition is achieved, then $u(k) = u^i(k)$
- If not, recalculate f using $u^i(k)$ for present and future values of the input. Set $i = i + 1$, and return to step 2.

4. IDENTIFICATION OF VOLTERRA MODEL

While trying to identify a linear input/output model for a linear MPC it is usually used an PRBS signal to feed the input of the system. Thus, with the output signal obtained it is possible to identify a model adjusting the resulting data set. For the linear case, this is an ordinary least squares problem. The actions required to identify a second order Volterra model are slightly different, but still sharing much of this straightforward method.

The main difference lies in the fact that a three level input signal is needed rather that a PRBS signal. However, for the rest of the identification procedure nothing else is changed, since the identification problem to be solved remains an ordinary least squares problem, and thus not needing any special formulation to identify a model (Pearson, 1999).

In order to identify a model for the PEM fuel cell it has been used a non linear simulator ((del Real *et al.*, 2007)). This model combines theoretical equations and experimental relations, resulting in a semi-empirical formulation. It describes the following areas: fluid dynamics in the gas flow fields and gas diffusion layers (oxygen, nitrogen, liquid water and vapor); thermal dynamics and temperature effects; and a novel algorithm to calcule an empirical polarization curve. As a result, this model can predict both steady and transient states due to variable loads (such as flooding and anode purges), as well as the system start-up.

Figure 1 shows the data set used to obtain the second order Volterra model for the system. The identification data was obtained for three different loads for the fuel cell, represented by the current supplied, starting at 5 A and ending at 30 A. The manipulated variable, that is, the compressor voltage, is set to three different levels for each operation point, so that the non linear behavior of the plant, mainly the nonlinear gain can be extracted through the identification procedure. On the other hand it can be seen how the output variable can take values between 1.5 and 3.8.

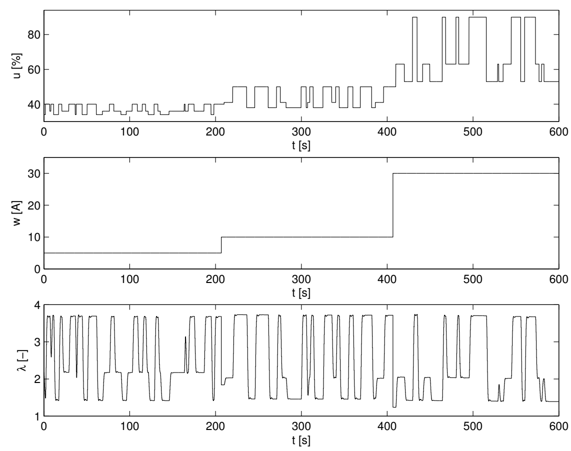

Fig. 1. Identification Data Set

The Volterra model that was chosen for this process was taken accordint to the following truncation orders shwon in table 2.

Table 2. Model parameters

Parameter	Value
N_1	40
N_2	20

The values for the model are presented in figures 2 and 3. The linear parameters of the model (2) are displayed in (2), in which the typical impulse response for a linear model can be recognized. On the other hand, the second order parameters are presented in 3, where it can be seen the fading memory of the system through the decay of the parameters value towards zero while time passes. This behavior could be interpreted as an extended second order impulse response.

Finally in 4 the results of identifying the system are shown. In the upper graph the identification data set is presented with the outcome of the model, whereas in the bottom plot, the validation set is displayed.

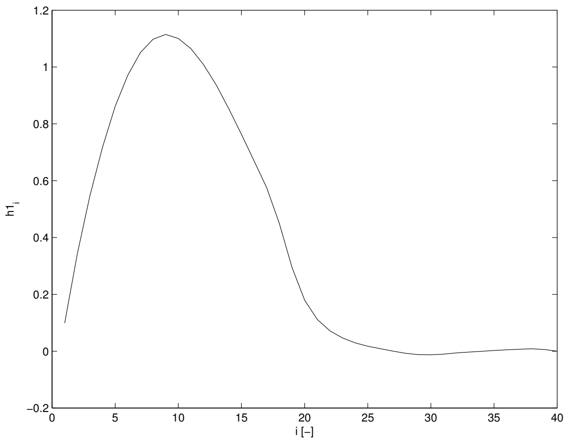

Fig. 2. Volterra model: Linear parameters

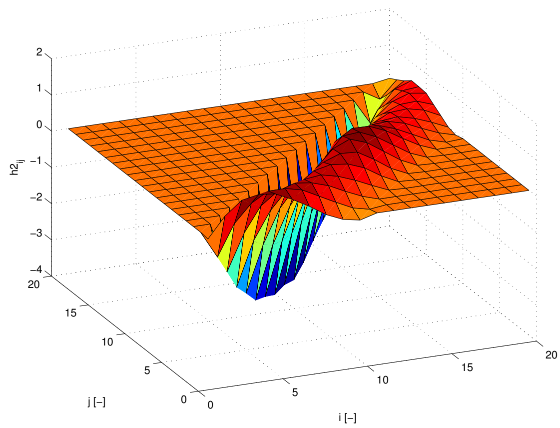

Fig. 3. Volterra model: Second order parameters

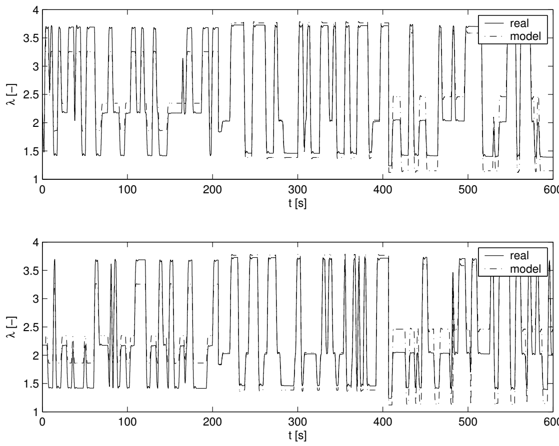

Fig. 4. Outcome of model. Identification (top) and validation (bottom) sets

5. CONTROLLER PERFORMANCE

Finally, the Volterra model based predictive controller was implemented in Simulink and applied to the mathematical model of the fuel cell. A second controller, a linear model predictive controller, was used to obtain simulation results allowing comparison between the linear and non linear controllers. During the simulations, different steps in the measurable perturbation w (current in the fuel cell) were applied.

In first place, the linear predictive controller was tested with the fuel cell model. The controller is based on a convolution model with $N_1 = 40$ and $N_1 = 1$ parameters considering the influence of input u and perturbation w. As prediction horizon $N_p = 40$ and as control horizon $N_u = 10$ was used. For the weight parameter λ, considering the control action in the cost function, a value of 1000 was chosen. Figure 5 shows the simulation results of the fuel cell model controlled by the linear controller. As can be seen in the results, the linear controller is able to compensate the discrepancy between the oxygen excess ratio and its reference. In steady state, the linear controller avoids errors and stabilizes the oxygen excess ration in $\lambda = 2$. On the other hand, the results show clearly that the controller changes its behavior for different values of the perturbation. For low values of the perturbation, the output of the system tends to oscillate. For high values of w, the system response gets very slowly needing nearly 10 seconds to reach steady state.

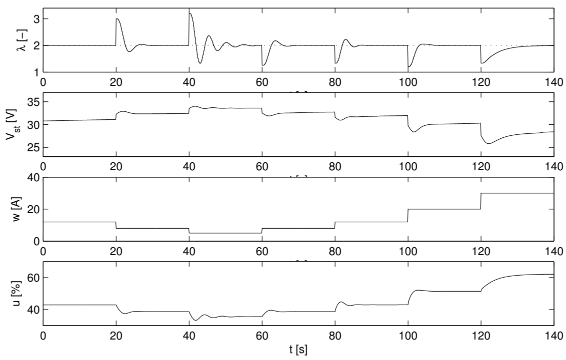

Fig. 5. Results of the linear controller

In second place, the designed nonlinear controller was applied to the simulation model. For the different horizons and the weighting parameter the same values as in the case of the linear controller were used. The results in figure 6 show that the nonlinear controller has a fast reaction on errors in the oxygen excess ratio λ provoked by sudden changes in the perturbation w. It can clearly be seen that the output of the system controlled by the nonlinear controller oscillates less for low values of the perturbation than in the case of the linear controller. For high perturbation values, the reaction of the system is considerably faster and needs only 5 seconds to reach steady state. With respect to the computational effort of the nonlinear controller, the results show that the calculation of the new control action requires in the maximum case 10 iterations (after a sudden change in the perturbation) but normally only 1 to 3 iterations (nearly steady state). In the maximum case of 10 iterations, the used computer (Pentium

Error	linear	nonlinear
J	168.13	131.74

Table 3. Comparison of the sum of square errors during the simulation with the linear and nonlinear controller.

4 with 3 GHz) needed 0.0244 seconds and stayed clearly below the sampling time of 0.1 seconds.

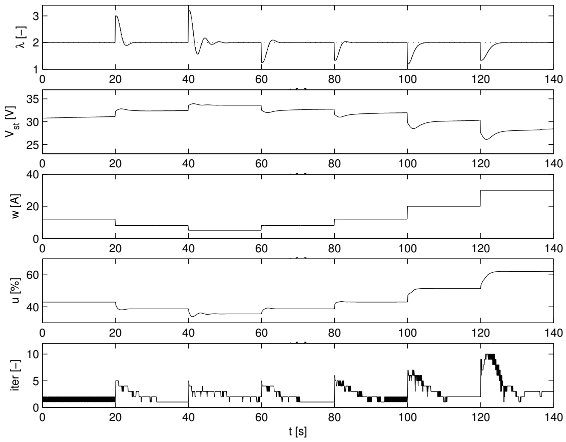

Fig. 6. Results of the non linear controller

For better comparison of the results, the oxygen excess ratio of the simulations with the linear and the nonlinear controller is shown in 7. As can be seen, both controllers show a similar behavior for intermediate values of the perturbation. For low and high values, the nonlinear controller shows a better control behavior and the oxygen excess ratio reaches steady state rapidly with few oscillation. Finally, to give an idea of the control quality, the sum of the square errors was calculated:

$$J = \sum_{i=1} (s(i) - y(i))^2$$

The resulting errors obtained in the simulation with the linear and the non linear controller can be seen in table 3.

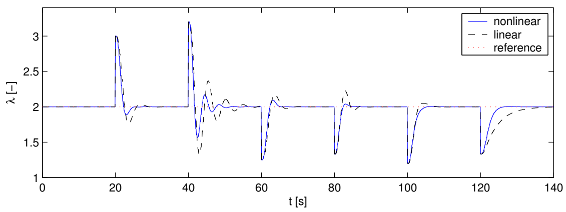

Fig. 7. Direct comparison of the oxygen excess ratio controlled by the linear/non linear controller.

6. CONCLUSIONS

This paper has presented a non linear model predictive controller based on Volterra models for a PEM fuel cell. In order to test the performance of the controller it was tested under simulation on a full non linear model of the real process. The advantages in performance obtained have been shown when compared to a linear counterpart. The complexity introduced by the non linear controller does not jeopardize the solution of the optimization problem, being able to deliver the control signal within the required time.

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Network of Integrated Biomeasurements and Control via Intranet and SMS

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The NIBCIS-system (Network of Integrated Biomeasurements and Control via Intranet and SMS) was developed for data acquisition, data integration and combining distributed measurements during bioreactor process monitoring. In general, it is advantageous that all data are collected *on line* at one place and shared *on line* with other applications, such as Matlab/Simulink (MathWorks) based distributed controllers. Data services, remote monitoring and control of ongoing cultivations were approached by microcontroller-based interface module and device specific software. In addition, information delivery via SMS mobile phone was added to the system. The technologies were developed around commercial software called MFCS (Multi Fermentor Controlling System), which is now extended to accommodate many different devices with greater ease and flexibility. Various measurement devices were connected and synchronized to an integrated system with many bioreactors. Integrated devices were for example biomass monitoring, mass spectrometer and glucose control.

The microcontroller (ATMEGA8535) based interface module capable of communicating with a PC using a standard serial port (RS232) was developed for devices using other than serial data interface, e.g. analogue signals. A simple single side circuit board was designed so that it could be used for multiple purposes without changing the layout. This feature was achieved by leaving a small raster board area to the other end of the circuit board, which can be used for the unique components required for a specific device module. Modular program for microcontrollers was developed using C-language.

The device specific software was developed for each laboratory device integrated to the system by using Visual Basic 6.0 at Windows 2000/XP environment. The device specific software is able to communicate with the target device as required in each case. In most cases communication is done via serial port either directly or with the help of the interface module. However communication via DDE (Dynamic Data Exchange) interface and local web server is also used. Data transferring to MFCS via software interface (MFCSAPDA) were implement for all device specific software. System flexibility was increased by developing a server application (mfcsServerPro) for MFCS capable of converting the software interface to a simple network TCP/IP interface. This implementation made it possible to share and collect *on line* data via intranet and distribute measurement devices so that they could be connected to any PC in the laboratory intranet. Overview of data flow in the current system is illustrated in Figure 1.

Currently more than ten different external laboratory devices are integrated to the system built around MFCS and eleven bioreactors (some bioreactors are considered as a laboratory devices as show in Figure 1 due to indirect communication with MFCS and use of interface module). The concept of device specific software with uniform user interfaces made rapid development possible and proven to be practical also from user point of view. The microcontroller-based interface module proved to be a simple and inexpensive method for integrating devices with analogue interface.

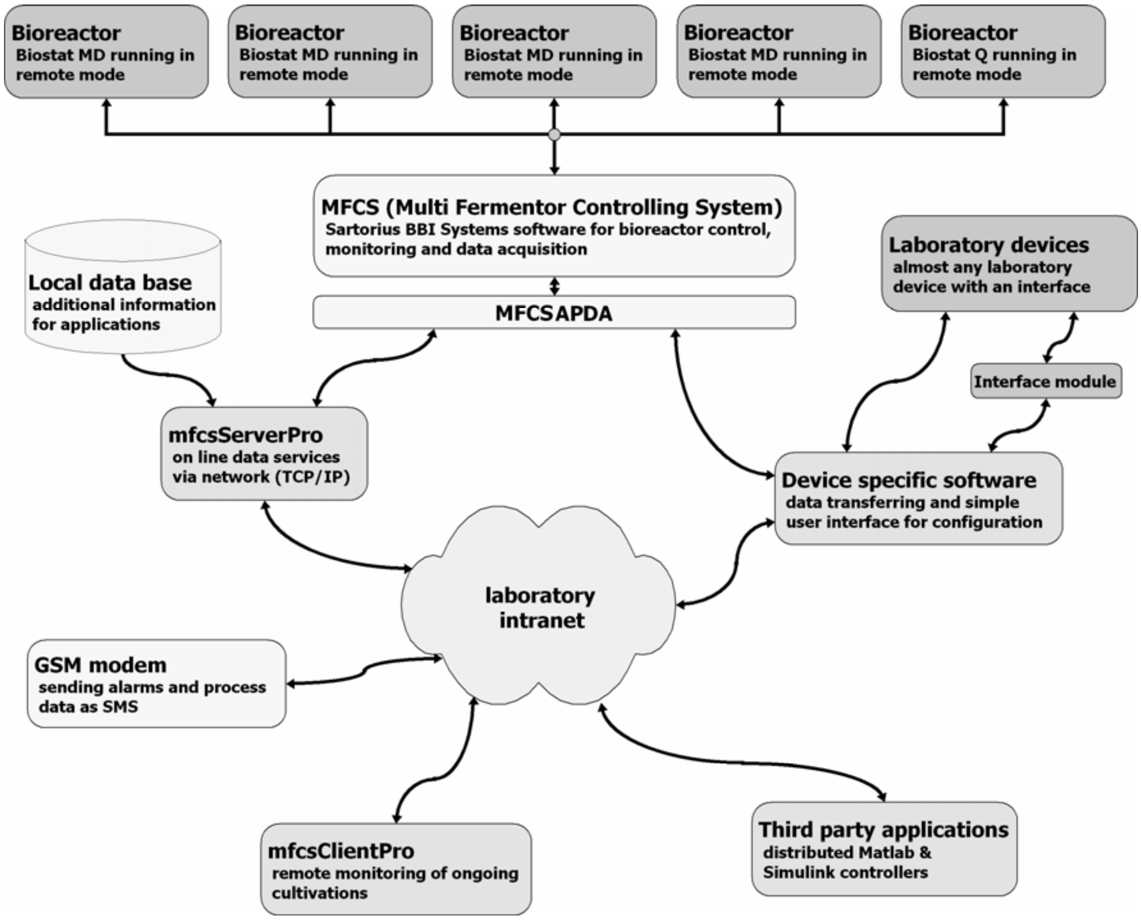

Figure 1. Data flow in the current system. All arrows present data flow and data can flow through any box if not terminal. Alternative routes are present parallel.

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ISBN 978-951-22-8913-4
ISSN 1455-4046