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Roll-out of Model Based Control with Application to Paper Machines

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Roll-out of model based control with application to paper machines

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Thesis submitted to the
Norwegian University of Science and Technology
for the degree of Dr.ing.

Contents

Preface and acknowledgments

This thesis is submitted in partial fulfillment of the requirements for the degree of *doktor ingeniør* (dr.ing.) at the Norwegian University of Science and Technology (NTNU) and Telemark University College (HIT). The work is carried out with financial support from the Research Council of Norway through project 134557/432, and Norske Skog Saugbrugs through the project "Stabilization of the wet end at PM6". This financial support is gratefully acknowledged.

In 1999, the intention of this work was to investigate "*Methods for efficient roll-out of robust model based control in the process industry*"[1], i.e. how do we efficiently develop and apply a model based controller for a number of similar processes or process units. Four terms were to be focused on: modeling, robust control, roll-out, and a case study. The reader of this thesis will find lots of pages on modeling and model predictive control (MPC), none on robust control, some pages on roll-out, and almost all pages related to the case study: paper machines. Although it was not the intention to have such a strong focus on the case study, it seemed that with such practical issues as modeling, control and roll-out in the process industry, it was beneficial to discuss an actual industrial plant rather than some fabricated model. Thus, the title of this thesis was changed to "*Roll-out of model based control with application to paper machines*" to better reflect the focus of this work. Nevertheless, it is my hope and belief that this work should also be of interest beyond the pulp and paper community, as modeling, control, and roll-out have many similarities across various process industries.

I have spent the time from September 1999 to December 2002 working on this thesis, and I have had the pleasure of meeting and interacting with so many brilliant and nice persons from both industry and colleges/universities. A number of them deserve special recognition.

First I would like to thank my supervisor associate professor Bernt Lie, at Telemark University College (HIT). Thank you for encouraging me to study for the degree of dr.ing, for providing financial funding for my study, and for guidance, tips, hints, corrections, and valuable discussions along the way. It is funny, and a bit frustrating, thinking how I imagined that I would really be an expert in a niche after finishing my doctoral degree, only to find out that I still have "a world" to learn before I have the wealth of knowledge that you have.

I deeply appreciated having two co-supervisors with great professional skill to rely

[1] Working title for this thesis.

on. Thank you associate professor Rolf Ergon (HIT) for always being helpful and interested in my work, for functioning as supervisor while Bernt was on sabbatical leave, for collaboration on two M.Sc. theses and one conference article, and for pleasant lunch breaks and discussions. Although my contact with dr. Steinar Sælid (Prediktor) has been less frequent, I want to thank him for his tips and comments on modeling and his repeated comment "make the model simpler" which I know have been very important.

The person that I have had most professional contact with during these years is Mr. Roger Slora from Norske Skog Saugbrugs. He took the initiative to, and is the project leader for, the "Stabilization of the wet end at PM6" project at Norske Skog Saugbrugs. I am very grateful that I was given the opportunity to work in this exiting project, with its enthusiastic, positive, and technically skilled leader. And I feel privileged to have had an industrial partner so eager to turn theoretical studies into practical implementations. I would also like to thank the other project members: Mr. Jan Tore Gjøby (specialist on the Saugbrugs DCS system), Mr. Øystein Jonassen (specialist on the Saugbrugs measurement devices), Mr. Hans Erik Høydahl (chemistry specialist from Norske Skog Research), and Mr. Hans Hoel (chemistry specialist from Norske Skog Research), as well as managers at Saugbrugs that dared to invest time and money in the project; specifically Mr. Eilert Vikesland (Development Manager), Mr. Per Ivar Berg (now Mill Manager at Norske Skog Follum), and Mr. Vidar Backstrøm (Senior Production Manager).

A couple of years ago, associate professor Bernt Lie and his doctoral students formed The Cybernetics Research Group (CYNERG at www.hit.no/cynerg) at Telemark University College (www.hit.no). As of today the CYNERG doctoral students are Glenn-Ole Kaasa (whom I shared office with), Martha Dueñas Díez, and Beathe Furenes. Thank you fellow CYNERG doctoral students for warm and joyful memories, for making the lunch break a highlight of the day, and for friendship and support during good and hard times.

I would also like to thank Dr. Hong Wang for being my kind host during my short visit to UMIST Department of paper science in December 2001, associate professor David Di Ruscio at HIT for help on system identification issues, Anders Veberg from Prediktor AS for MPC collaboration, Glenn-Ove Forsland and Ståle Enes for their contributions through their M.Sc. theses, process engineer Tor Gunnar Heggli at Norske Skog Skogn for providing data and information about PM3, colleagues in the department of process automation at HIT for providing a fine working environment, the administration at the faculty of technology at HIT (Trine Ellefsen, Stig F. Nilsen, Eldrid Eilertsen, and more) for always being helpful with keeping account of my income and expenditure, paying my bills, and other non-technical problems, and the library personnel at HIT, Porsgrunn campus, for providing any obscure article that I have requested.

Finally, I am indebted to my wife Randi Katrine for her support during these years, and to our children Daniel and Emilie for keeping my mind off of modeling and control for at least a few hours every day.

Porsgrunn, December 2002
Tor Anders Hauge

Summary and conclusions

Abstract A mechanistic nonlinear model of the wet end of paper machine 6 (PM6) at Norske Skog Saugbrugs, Norway has been developed, and used in an MPC application. The MPC provides reduced variability in many key variables, and better efficiency through faster grade changes, start ups, and improved control during periods of poor measurements. The model and controller can be rolled-out to other paper machines, as found by studying and fitting the model to data from PM4 at Norske Skog Saugbrugs, and PM3 at Norske Skog Skogn, Norway. No changes to the model, except for parameter values, were introduced, and still the validation results were good. The time spent on fitting and validating the PM6 model to PM4 and PM3 are approximately 1% of the time spent on developing the original model. This should be a strong incentive for focusing on mechanistic modeling in industries were there are many similar production lines or units.

Motivation Many large- and medium sized industry companies have a number of more or less similar process-units for processing of raw materials or production of finished products. An industrial company which has invested, or is about to invest, in advanced model based control in one of their units / factories, would benefit economically if the model and controller could be efficiently rolled-out at similar units. The main idea of this thesis is to develop a model and a controller for an industrial process, and then investigate how the model and controller can be applied to similar processes. Paper machine 6 (PM6) at Norske Skog Saugbrugs, Norway, is used as a case study for modeling and control throughout the thesis, and the PM6 model is also applied at Norske Skog Saugbrugs PM4, and PM3 at Norske Skog Skogn, Norway.

The papermaking process is the only process studied in this thesis, however the field of roll-out should be of interest also to other industries. For example Borealis (www.borealisgroup.com) has many polymer reactors for producing plastics raw materials, Norsk Hydro (www.hydro.com) has many plants for fertilizer production, and Icopal (www.icopal.com) has many production lines for extrusion of plastic pipes. The idea of efficient roll-out of models is not entirely new, e.g. (Glemmestad, Ertler & Hillestad 2002) emphasize the advantage of reusing the models developed at Borealis, and many commercial simulators include model libraries of process units intended for reuse.

The control method chosen in this work is model predictive control (MPC). The reason for choosing MPC is that it is perhaps the only advanced model based control scheme used to any extent in the industry, there are commercially available software systems for implementation, and the reported payback time is low (e.g. 3 months in (Bassett & Van Wijck 1999)).

Modeling Two basic modeling approaches are *mechanistic* modeling and *empiric* modeling. An empiric model is entirely based on experimental data and an appropriate model structure, and often requires little knowledge of the system to be modeled. A mechanistic model is a model built from basic principles of physics, chemistry, biology, etc., by writing down conservation or balance equations. Obviously this requires extensive knowledge of the process to be modeled. Emphasis has been on mechanistic modeling of PM6, however empiric modeling is also carried out and described in this thesis.

A high order mechanistic model of PM6 was developed and implemented in Matlab. The objective was to make a model of a limited part of PM6, which were suitable for model predictive control (MPC) , captured the essential dynamic behavior of the process, and was applicable over a wide range of operating conditions. The output variables are the basis weight, the paper ash content and the white water total concentration. To make the model suitable for model based control, reduced order models were developed and fitted to experimental and operational mill data. The fitted models where validated with historical operational data.

An augmented suboptimal Kalman filter has been developed at PM6 for estimating the states and some of the parameters in the paper machine model. Three biases have been selected for on-line estimation in the paper machine model. The first two are biases in the estimated total- and filler thick stock consistencies. These disturbances are estimated using a ballistic estimator, and thus they are assumed to be good candidates for having time-varying biases. The third bias estimated on-line is for the total wire tray concentration, i.e. a bias in one of the outputs. In theory, and in the true Kalman filter, the noise characteristics of the process should be found and used in the Kalman filter equations. However, these characteristics are hard, if not impossible, to find. Thus, a suboptimal Kalman filter was identified, where the noise characteristics where used as tuning parameters until satisfactory Kalman filter performance was obtained.

MPC The MPC was installed at PM6 in March 2002. During the first two months, the MPC, the Kalman filter and the model were continuously tuned, retuned, and validated in open and closed loop. Some structural changes were also made during these months. From May 2002, the MPC has been in operation more or less continuously. The process operators still have the original "pre-MPC era" control configuration available, but the MPC has been the preferred choice from the beginning. Furthermore, the operators have been very active in making suggestions for improvements and new features in the system. Some of these suggestions are implemented, and others are being considered for implementation.

A specific feature of the MPC implemented at PM6 is that the setpoints for new grades can be submitted to the MPC some time before the grade change. The operators can specify a grade change e.g. half an hour into the future, and see how the MPC will achieve the change: how the inputs will be manipulated to reach the new setpoints. In terms of gaining operator acceptance for the MPC, this feature of previewing the action taken by the controller has been very helpful.

Results The work carried out on modeling and MPC of PM6 has been part of a project called "Stabilization of the wet end at PM6". The main objective of the project was to increase the total efficiency by 0.47%. This is an objective that is hard to measure, due to many factors affecting the total efficiency. Thus, several sub-goals were defined which were assumed easier to measure and validate. The sub-goals, and results, concerning reduced variability are:

Variable	**Sub-goal (red. std. dev.)**	**Result**
Total cons. in the wire tray	60%	Achieved
Filler cons. in the wire tray	50%	Achieved
Total cons. in the headbox	50%	Achieved
Filler cons. in the headbox	35%	Achieved
Basis weight	20%	Not achieved
Paper ash	20%	Achieved
Paper moisture	20%	Achieved

These sub-goals were defined in 1999 when the project was initiated. In 2001 a new scanning device for measuring e.g. basis weight and paper ash was installed at PM6. This significantly improved the control of the basis weight using the "old" controllers. The results in the table above are calculated with the measurement devices as of 2002, comparing the old control configuration with the MPC control configuration. Exact numbers for the reduction in standard deviation are not given, as they vary from day to day, and from operator to operator.

In addition to reducing the variation in key paper machine variables, several other benefits are obtained using MPC. Some of these benefits arise from utilizing the developed model, not only for control purposes, but also as a replacement for measurements when these are not available or not trustworthy.

Previously, grade changes were carried out manually or partly manually (the setpoints were changed a number of times before they were equal to the new grade) by the operators. With a mechanistic model, applicable over a wide range of operating conditions, the grade changes are carried out using the MPC. This has resulted in faster grade changes and operator independent grade changes. During larger grade changes, the use of MPC results in less off-spec paper being produced during the change. Using a single mechanistic model, the grade change is handled in a straight forward fashion, as there is no need to switch between various local models.

The basis weight and paper ash outputs can not be measured during sheet breaks. Previously during sheet breaks, the flow of thick stock and filler were frozen at the value they had immediately prior to the break. Usually the sheet breaks last less than half an hour, and the output variables are not far from target values when the paper is back on the reel. However, occasionally the sheet breaks last longer periods and there may be e.g. velocity changes during the break, leading to off-spec paper being produced for a period after the paper is back on the reel. Another frequently experienced problem are large measurement errors immediately after a sheet break. With the MPC, the Kalman filter estimates the basis weight and paper ash during sheet breaks, and these estimates are used in the MPC as if no break had taken place. Thus, when the paper is back on the reel, the outputs are close to their setpoints.

Previously, the controllers were not set to automatic mode before the outputs were close to the setpoints, following a start up. With a model based controller using a mechanistic model with a wide operating range, the MPC is set to automatic mode early during start ups. This results in faster start ups, and less off-spec paper being produced.

Occasionally a special filler is added to the stock, to increase the brightness of the paper. During these periods the consistency measurements are not trustworthy as they are based on optical measurement methods. This problem is solved within the MPC / Kalman filter framework by neglecting the measured consistency, relying on the estimate alone. For each output, there is an option within the MPC to neglect the updating of states based on this output. This is done based on experience with periods of poor measurements, even when only standard filler is used.

The Kalman filter estimates are used in the MPC instead of the measurements. This leads to smoother controller action, and eliminates the need for additional filtering.

The model is augmented so that some key parameters/biases are updated automatically. This reduces the need for model maintenance off-line. However, should there be larger changes in the process, such as if the white water tank is removed, or a new retention aid is used, then it will probably be necessary to re-tune the model and controller.

Roll-out The possibility of reusing the PM6 model at other paper machines is investigated. The paper machines studied are PM4 at Norske Skog Saugbrugs, and PM3 at Norske Skog Skogn, Norway. PM6 is a new and modern paper machine producing SC (Super Calendered) magazine paper. PM4 also produce SC paper but the machine is older and smaller than PM6. PM3 produce newsprint and has a size comparable with that of PM6. Fitting and validation of the model to PM4 and PM3 were very promising. No changes to the model, except for parameter values, were introduced and still the validation results were good. The time spent on fitting and validating the PM6 model to PM4 and PM3 are approximately 1% of the time spent on developing the original model. This should be a strong incentive for focusing on mechanistic modeling in industries were there are many similar production lines or units.

Part I

Overview

Chapter 1

Introduction

1.1 Problem description

Many large- and medium sized industry companies have a number of more or less similar process-units for processing of raw materials or production of finished products. An industrial company which has invested, or is about to invest, in advanced model based control in one of their units / factories, would benefit economically if the model and controller could be efficiently rolled-out on similar units. The main idea of this thesis is to develop a model and a controller for an industrial process, and then investigate how the model and controller can be applied to similar processes. Paper machine 6 (PM6) at Norske Skog Saugbrugs, Norway, is used as a case study for modeling and control throughout the thesis, and the PM6 model is also applied at Norske Skog Saugbrugs PM4, and PM3 at Norske Skog Skogn, Norway. Pulp and paper is one of the largest and most important industries in Norway. In 2001, a total of 25 pulp and paper mills, and 7,300 employees contributed with aggregate sales of about NOK[1] 19,000 million. Approximately 90% of the Norwegian made paper and boards are exported, mostly to EU countries, but also to North America, Asia, Oceania, Eastern Europe, Latin America, and Africa (NPPA (The Norwegian Pulp and Paper Association) 2002) (Statistics Norway 2002*b*) (Statistics Norway 2002*a*).

The papermaking process is the only process studied in this thesis, however the field of roll-out should be of interest also to other industries. For example Borealis (www.borealisgroup.com) has many polymer reactors for producing plastics raw materials, Norsk Hydro (www.hydro.com) has many plants for fertilizer production, and Icopal (www.icopal.com) has many production lines for extrusion of plastic pipes.

The control method chosen in this work, is model predictive control (MPC). The reason for choosing MPC is that it is perhaps the only advanced model based control scheme used to any extent by the industry, there are commercially available software systems for implementation, and the reported payback time is low (e.g. 3 months in (Bassett & Van Wijck 1999)).

[1] NOK is the Norwegian currency. 1 Euro equals NOK 7.3, and 1 U.S. dollar equals NOK 7.3, November 22, 2002.

1.2 Previous work

There exists very little published material focusing on how to efficiently roll-out models and controllers in the industry. However, the idea of efficient roll-out of models is not entirely new, e.g. (Glemmestad et al. 2002) emphasize the advantage of reusing the models developed at Borealis, and many commercial simulators include model libraries of process units intended for reuse.

Empirical modeling or system identification of paper machines are reported in several papers and books. Some of these focus on so-called cross-directional (CD) modeling, i.e. a model for the profile across the paper web, e.g. (Featherstone, VanAntwerp & Braatz 2000), (Campbell 1997) and (Heaven, Manness, Vu & Vyse 1996). Others focus on the machine-direction (MD), i.e. changes in average values across the web, e.g. (Menani, Koivo, Huhtelin & Kuusisto 1998), (Noreus & Saltin 1998), and Papers A–B in this thesis. Note that only the MD modeling and control problem is studied in this thesis.

The reported works on mechanistic modeling of paper machines are in most cases constrained to smaller parts of the paper machine. However, (Rao, Xia & Ying 1994), (Larsson & Olsson 1996) and (Hagberg & Isaksson 1993) consider a larger part of the paper machine, e.g. the wet end and the wire, press, and dryer sections, although the chemistry involved in papermaking is not considered at all. Mechanistic models of a larger part of a paper machine which includes chemical modeling is found in (Shirt 1997), and Papers A–C in this thesis. In Shirt's work both chemical aspects, which include adsorption and flocculation, and physical aspects, which include drainage on the wire, refining, tanks, headbox, wire section, etc., are part of the overall model, although transportation delays in pipelines are neglected and not all aspects are presented in detail.

Several MPC implementations using multivariable empiric paper machine models are reported, e.g. (McQuillin & Huizinga 1995), (Lang, Tian, Kuusisto & Rantala 1998), (Mack, Lovett, Austin, Wright & Terry 2001), (Kosonen, Fu, Nuyan, Kuusisto & Huhtelin 2002), and (Austin, Mack, Lovett, Wright & Terry 2002). To the best of the author's knowledge, there exists no reported industrial MPC implementations utilizing a multivariable mechanistic model of the wet-end of the paper machine. Some industrial implementations of MPC with mechanistic models are known in other industry areas, e.g. (Qin & Badgwell 1998) and (Badgwell & Qin 2001) have reported a few implementations. Papers describing industrial implementations of MPC with mechanistic models are few, however (Hillestad & Andersen 1994) and (Glemmestad et al. 2002) report several applications to industrial polymer reactors. Several simulated examples exist, e.g. (Lee, Lee, Yang & Mahoney 2002), (Prasad, Schley, Russo & Bequette 2002), (Amin, Mehra & Arambel 2001), and (Schei & Singstad 1998), and also some applications to experimental test stands, e.g. (Ahn, Park & Rhee 1999) and (Park, Hur & Rhee 2002).

1.3 Outline of thesis

This thesis is composed of two parts. Part I basically gives an overview of the results obtained in the papers provided in Part II. However, a few results in Part I are not presented in any paper, either because they did not fit with the scope of the papers or because the results were not ready at the time of submission or publishing. Due to the structure of the thesis, some pieces of information are necessarily repeated several times; for example most papers have a section on description of the process. Also, some papers have similar scopes, notably papers A–C, and thus some information is repeated. Note that the papers in Part II are not entirely reproduced from the original source. In most papers a few corrections are made, e.g. pure spelling errors are corrected, and some papers are extended by adding material that was thought to be of interest in this thesis. The character of the modifications for each paper are given in Chapter 6 as well as at the start of each paper.

Chapter 2 gives an introduction to paper production. Some facts and statistics for the pulp and paper industry are given, and the production line from tree to paper is explained. Modeling aspects are discussed in Chapter 3, and results from the modeling of PM6 is summarized. Chapter 4 concentrates on model predictive control (MPC). The chapter consists of a short introduction to MPC, as well as results from the implementation at PM6, Norske Skog Saugbrugs, Norway. Chapter 5 summarizes the results from applying the PM6 model to other paper machines. Chapter 6 lists the papers appearing in the thesis, and Chapter 7 lists contributions not included in the thesis.

Abstract of Paper A A mechanistic model of order 528 of PM6 is implemented in Matlab. It is shown how the full scale model can be reduced by both system identification techniques and by utilizing physical knowledge about the process. The long term prediction abilities of the various reduced order models are compared with the output from the 528 order model, highlighting some distinct features of the various models.

Abstract of Paper B This paper summarize some of the results from Paper A, and also provides results from using industrial data from PM6. Closed loop experiments on PM6 is described and carried out, and empiric models are identified and validated. A solution for estimating missing measurements during sheet breaks is presented and demonstrated with simulations.

Abstract of Paper C Details of the mechanistic model of PM6 is presented. The model is developed as a foundation for the control of three selected variables, the basis weight, the paper ash content and the white water total concentration. The model is of high order and reduced order models are developed and fitted to experimental mill data. The fitted models are validated with historical operational data.

Abstract of Paper D Results from a controllability analysis, based on a linearized PM6 model, is given. The analysis indicates the necessity of process operators acting on measured disturbances to avoid input saturation. A commercially available MPC algorithm based on a linear model is modified to handle the nonlinear model, and to allow for future setpoint changes.

Abstract of Paper E Four quadratic programming (QP) formulations of model predictive control (MPC) are compared with regards to ease of formulation, memory requirement, and numerical properties. The comparison is based on two example processes: A linearized PM6 model, and a model of the Tennessee Eastman challenge process; the number of free variables range from 150–1400. Five commercial QP solvers are compared. Preliminary results indicate that dense solvers still are the most efficient, but sparse solvers hold great promise.

Abstract of Paper F The PM6 model is used in an MPC implementation. The MPC uses an infinite horizon criterion, successive linearization of the model, and estimation of states and parameters by an augmented Kalman filter. Variation in important quality variables and consistencies in the wet end have been reduced substantially, compared to the variation prior to the MPC implementation. The MPC also provides better efficiency through faster grade changes, control during sheet breaks and start ups, and better control during periods of poor measurements. From May 2002 the MPC has been the preferred controller choice for the process operators at PM6.

Abstract of Paper G The possibility of reusing the PM6 model at other paper machines is investigated. The paper machines studied are PM4 at Norske Skog Saugbrugs, and PM3 at Norske Skog Skogn, Norway. PM6 is a new and modern paper machine producing SC (Super Calendered) magazine paper. PM4 also produce SC paper but the machine is older and smaller than PM6. PM3 produce newsprint and has a size comparable with that of PM6. Fitting and validation of the model to PM4 and PM3 data were very promising. No changes to the model, except for parameter values, were introduced and still the validation results were good. The time spent on fitting and validating the PM6 model to PM4 and PM3 data are approximately 1% of the time spent on developing the original model. This should be a strong incentive for focusing on mechanistic modeling in industries were there are many similar production lines or units.

1.4 Main contributions

The main contributions of this thesis are:

- A mechanistic model of the wet end of a paper machine is developed, fitted with data, and validated: Chapter 3, and Papers A–C.

- Extensions to a previously published infinite horizon criterion by (Muske & Rawlings 1993). Extensions include e.g. the possibility to specify future reference changes, direct input to output term, and inclusion of measured disturbances. Chapter 4, and Papers D–F.
- Algorithm for nonlinear infinite horizon MPC, based on successive linearization of mechanistic model: Chapter 4, and Paper F.
- Industrial application of nonlinear MPC with a mechanistic model: Chapter 4, and Paper F.
- Investigation of the roll-out potential of the mechanistic model: Chapter 5, and Paper G.

Chapter 2

Paper production

2.1 Facts and statistics

Pulp and paper industry in Norway and worldwide (Sources: (NPPA (The Norwegian Pulp and Paper Association) 2002), (Statistics Norway 2002*b*), and (Statistics Norway 2002*a*))

Pulp and paper is one of the largest and most important industries in Norway. In 2001, a total of 25 pulp and paper mills, and 7,300 employees contributed with aggregate sales of about NOK[1] 19,000 million. Approximately 90% of the Norwegian made paper and boards are exported, mostly to EU countries, but also to North America, Asia, Oceania, Eastern Europe, Latin America, and Africa.

On a worldwide basis, the production of paper and boards in Norway is not large. The total world production of paper and board in the year 2000 was 323 million tons, and the Norwegian share was "only" 2.4 million tons. The largest producer is by far USA with a production of 85.5 million tons, with other large producers being Japan, and Canada. Finland and Sweden are also large on a world wide basis, producing above 10 million tons each.

Norske Skog (Source: (Norske Skog 2002))

The Norske Skog group is the world's second largest producer of newsprint, and the world's third largest supplier of printing paper. Norske Skog employs 14,000 people in 24 production units (full- and part-owner) spread around Europe, North and South America, Asia and Oceania. The operating revenue for 2001 exceeded NOK 30,000 million, and the earnings were close to NOK 2,500 million. In terms of area, the European revenue accounts for nearly half the total revenue. In terms of product, the newsprint is by far the largest contributor accounting for 68% of the revenue, and pulp and SC[2] magazine paper accounts for 10% each.

[1] NOK is the Norwegian currency. 1 Euro equals NOK 7.3, and 1 U.S. dollar equals NOK 7.3, November 22, 2002.

[2] SC = Super Calendered

Norske Skog Saugbrugs (Source: (Sandersen 1999))

Founded in 1859, and a part of the Norske Skog group since 1989, Norske Skog Saugbrugs is today one of the world's leading producers of SC magazine paper. Saugbrugs has a market share in Europe and USA of about 10%. As much as 99% of the paper is sold for export, and the turnover is approximately NOK 2,500 million. The total production capacity at the Saugbrugs mill is 550,000 tons, and PM6 (Paper Machine 6) accounts for more than half the total capacity. PM6 was build by Valmet and started up in 1993. The production speed is around 1500 m/min, and the paper width is 8.62 m. Many different grades are produced, e.g. the basis weight[3] range from 40-60 $\mathrm{g/m^2}$.

2.2 From tree to paper

2.2.1 The PM6 production line

Figure 2.1 shows the PM6 production line. The trees are transported from the woodyard to the groundwood mill and TMP (Thermo Mechanical Pulp) plant, where pulp[4] is produced. The stone groundwood mill produce pulp by pressing a piece of wood lengthwise against a wetted, roughened grinding stone revolving at high speed. In the TMP plant, pulp is produced from chips of wood by pressurized steam pretreatment and shredding, and defibering between rotating discs in refiners. The pulp is bleached and stored in large tanks. The pulp is then transported to the wire section and blended with chemical pulp, clay (filler particles), color, and other chemicals on the way. Most of the fiber and filler particles are retained on the wire where they form a thin mat. The mat becomes the paper sheet when water is pressed out of it in the press section, and dried in the dryer section. The paper sheet is then accumulated on the pope (or reel), and transported to the super calenders where properties like smoothness and gloss are added. The paper sheet is cut into appropriate size, wrapped and transported to the end-users (publishing companies, printing offices, etc.).

A proper introduction to the various stages in papermaking, and other issues as well, can be found in e.g. (Smook 1992). Books more focused on chemical issues in papermaking are e.g. (Roberts 1996*a*), and (Roberts 1996*b*).

The content of this thesis focuses on the PM6 production line approximately from the outlets of the storage tanks and to the paper is rolled-up on the pope. This sub-process is described next.

2.2.2 The thick stock and short circulation of PM6

A simplified drawing of the thick stock and short circulation of PM6 is shown in Figure 2.2. Cellulose, TMP (thermomechanical pulp) and broke (repulped fibers and filler from sheet breaks and edge trimmings) are blended in the mixing chest. The stock is

[3] Basis weight is the weight per area of finished paper.
[4] Pulp is a fibrous mass.

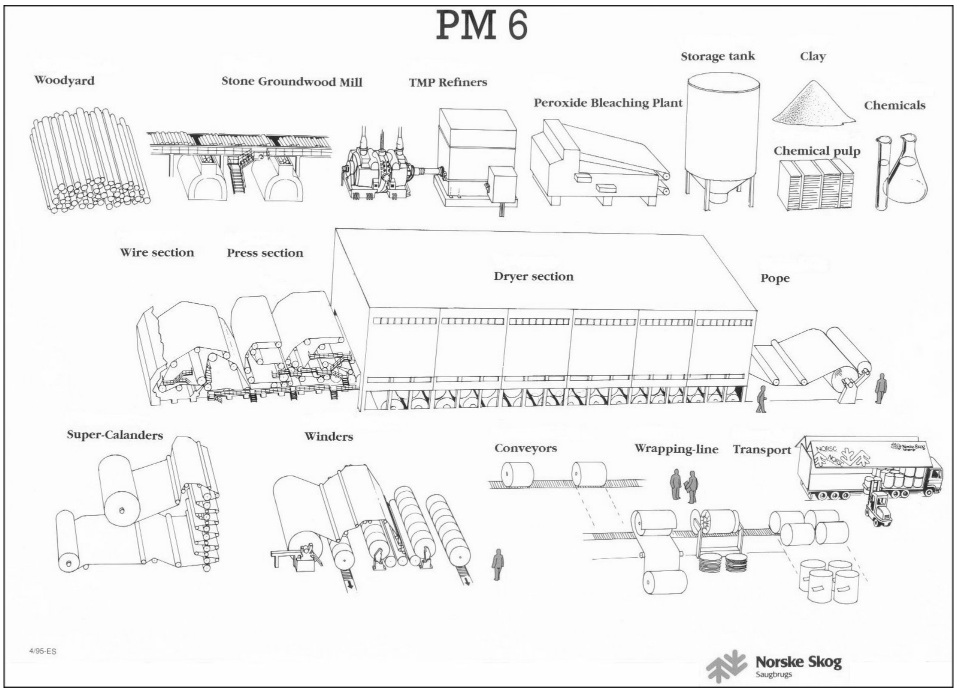

Figure 2.1: PM6 production line (From Norske Skog Saugbrugs leaflet).

fed to the machine chest with a controlled total consistency[5]. Filler is added between the mixing and machine chests. The fillers used in paper production depend on the end-user requirements; typical fillers are kaolin, chalk, talc, and titanium dioxide (Bown 1996). About two thirds of the filler particles used at PM6 are added to the thick stock; the rest is added at the outlet of the white water tank. The flow to the machine chest is large in order to keep the level of the machine chest constant, and an overflow is returned to the mixing chest. The total consistency in the mixing and machine chests are typically around $3-4\%$, which is considerably higher than consistencies later on in the process, and thus the stock from the machine chest is denoted the "thick stock".

The thick stock enters the "short circulation" in the white water tank. Here, the thick stock is diluted to 1-1.5% total consistency by white water[6] and a recirculation flow from the deculator. Filler is added to the stock just after the white water tank. The first cleaning process is a five stage hydrocyclone arrangement, mainly intended to separate heavy particles (e.g. sand and stones) from the flow. The *accept* from the first stage of the hydrocyclones goes to the deculator where air is separated from the stock. The second cleaning process consists of two parallel screens, which separate larger particles (e.g. bark) from the stock. Retention aid is added to the stock at the outlet of the screens. The retention aid is a cationic polymer which, amongst others, adsorb onto anionic fibers and filler particles and cause them to flocculate. The flocculation is a key process for retaining small filler particles and small fiber fragments on the wire, although the significance of mechanical entrapment of non-flocculated filler and fines seems to be somewhat controversial in the literature. For example (Van de Ven 1984) found (theoretically) that mechanical entrapment was low, while (Bown 1996) reports that mechanical entrapment can be a dominant mechanism. In the headbox, the pulp is distributed evenly onto the finely meshed woven wire cloth. Most of the water in the pulp is recirculated to the white water tank, while a share of fiber material and filler particles form a network on the wire which will soon become the paper sheet. The pulp flow from the white water tank, through the hydrocyclones, deculator, screens, headbox, onto the wire and back to the white water tank is denoted the "short circulation".

In the wire section, most of the water is removed by drainage. In the press section, the paper sheet is pressed between rotating steel rolls, thus making use of mechanical forces for water removal. Finally, in the dryer section, the paper sheet passes over rotating and heated cast iron cylinders, and most of the water left in the sheet is removed by evaporation. The paper is then rolled up on the reel before it is moved on to further processing.

[5] The total consistency is the weight of solids (i.e. filler particles and fiber) divided by the total weight of solids and water.

[6] White water, which is stored in the white water tank, is the drainage from the wire.

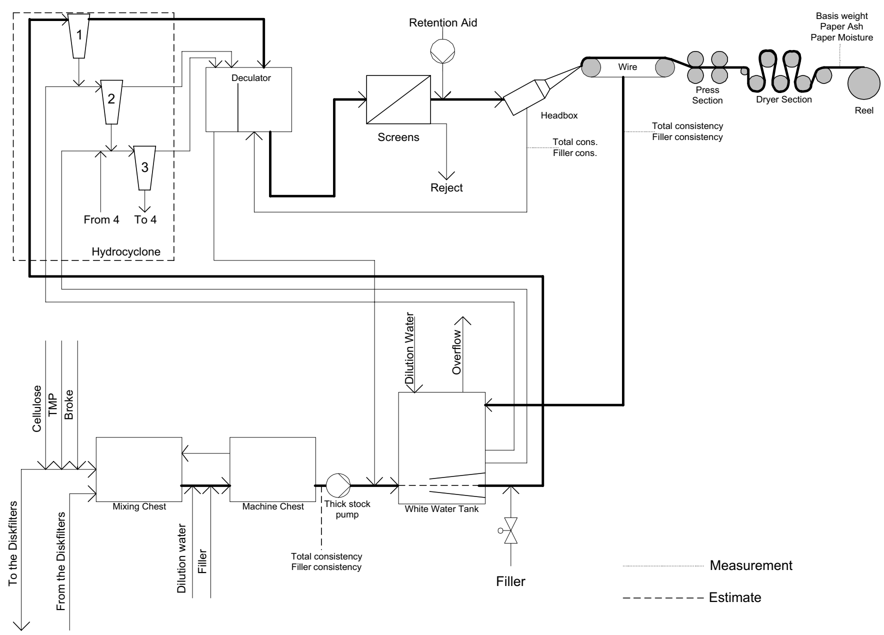

Figure 2.2: A simplified drawing of the thick stock and short circulation of PM6. More details are available in Paper C.

Chapter 3

Modeling

A model of the process is the foundation for every advanced control algorithm. Given a good model of a process, there are probably a number of algorithms that will provide excellent control of the process, and given a poor model of a process, there are probably no algorithms that will provide good control of the process. Also, given a good advanced control algorithm, there are often no models available for the specific process or process unit of concern. Thus, today the key factor for success in advanced control is the development of a reliable and good process model, or as the following closing sentence in a paper put it:

> Nowadays control is easy, modelling will always be the nut to crack...
> (Richalet, Estival & Fiani 1995, page 942)

It should be emphasized that even if a perfect model is available, several limitations to control performance may occur. These limitations may arise from e.g. input constraints, and right half plane (RHP) zeros (Skogestad & Postlethwaite 1996). In practice, the model is not perfect, and additional limitations due to model uncertainty are always present.

Two basic modeling approaches are *mechanistic* modeling and *empiric* modeling. Next, these approaches are presented in more detail.

3.1 Empiric modeling

3.1.1 Introduction

An empiric model is entirely based on experimental data and an appropriate model structure, and often requires little knowledge of the system to be modeled. In the literature one often encounters terms like black box modeling, system identification, time series analysis, and behavioral modeling. All these terms basically mean the same as empiric modeling, the term which is used in this thesis. Introductory and advanced text books on empiric modeling are e.g. (Nelles 2001), (Ljung 1999), (Walter & Pronzato 1997), (Söderström & Stoica 1989), and (Box, Jenkins & Reinsel 1994).

Empiric modeling methods can be further categorized in nonparametric and parametric methods.

Nonparametric methods Nonparametric methods typically provide a pictorial representation of the model. These methods provide information about the process, but the models need to be converted to parametric models before they can be useful for e.g. control purposes. Two common nonparametric methods are, see e.g. (Ljung 1999) and (Söderström & Stoica 1989):

- Transient analysis – Plots of impulse responses or step responses provide information about the delay, gain, and time constants of simple systems.
- Frequency analysis – Sinusoidal input signals are applied to the process, and phase and amplitude are calculated. Various frequencies are applied and the result is plotted in e.g. a Bode diagram.

Parametric methods Although an iterative procedure, several steps in building a parametric empiric model can be identified. The steps below are not necessarily performed successively, see e.g. (Ljung 1999) and (Walter & Pronzato 1997):

1. Choose inputs and outputs
2. Collect experimental data
3. Pretreatment of data, search for outliers, and trends.
4. Choose model structure (state space model, neural net, transfer function, etc.)
5. Choose model order
6. Choose criterion for optimization of model fit
7. Calculate parameters in model, based on optimization of the criterion
8. Validate model

Within the control community, the prediction error method (PEM) is probably the best known criterion:

$$\hat{\theta}_{PEM} = \arg\min_{\theta} J_{PEM}(\theta), \tag{3.1}$$

where $\hat{\theta}_{PEM}$ is the estimated parameter vector that minimize the criterion $J_{PEM}(\theta)$. The criterion is a function of the l-step-ahead prediction error

$$\varepsilon = \hat{y}(k|k-l) - y(k), \tag{3.2}$$

where $\hat{y}(k|k-l)$ are the predicted outputs at time k based on data up to time $k-l$, and $y(k)$ are the measured outputs at time k. Typically the squared prediction error is used

$$J_{PEM}(\theta) = \sum_{k=0}^{N-1} \varepsilon^T Q_k \varepsilon, \tag{3.3}$$

where Q_k is a weight matrix. One-step-ahead predictions are often preferred for models for control, while $l = k + 1$ is commonly used when long term prediction abilities are required, such as in model predictive control. Note that setting $l = k+1$ means pure curve fitting, i.e. fitting the simulated model output to the measured data. Normally one need to use some iterative search algorithm, like e.g. Gauss-Newton, to find the optimal parameter vector, however if the model is linear in the parameters then the optimal parameters can be found without iterations by the least squares method.

A statistically founded competitor to PEM is the maximum likelihood method (MLM):

$$\hat{\theta}_{MLM} = \arg\max_{\theta} J_{MLM}(\theta), \tag{3.4}$$

where $\hat{\theta}_{MLM}$ is the estimated parameter vector that maximizes the criterion $J_{MLM}(\theta)$. The criterion is the likelihood function, reflecting the likelihood of the measured data. If the measured data are independent random variables, then the likelihood is the joint probability density function of these data

$$J_{MLM}(\theta) = f_y(y_{\text{obs}}|\theta), \tag{3.5}$$

where y_{obs} is the measured data, and $f_y(y_{\text{obs}}|\theta)$ is the probability that the observations y_{obs} should take place with a given parameter vector θ. For a dynamic system, the observations are usually dependent. However, using an estimator, the prediction errors are assumed independent and with a certain probability density function. In such a case the MLM can be seen as a special case of the PEM.

Subspace methods Subspace methods are parametric methods, as the output from such methods are state space models. However, the subspace methods have some distinct features and it makes sense to present them as a unique method. (Ljung 1996) characterize subspace system identification as the most interesting development in system identification in the past decade. There are a number of different subspace algorithms available, such as DSR, CVA, N4SID, and PO-MOESP. Complete linear state space models are identified without prior parametrization, except for the system order which can be decided upon by studying singular values, and without iteration (Di Ruscio 1997), (Van Overschee & De Moor 1996). The algorithms are very fast and reliable because no iterations are performed.

The probably best known algorithm is N4SID due to its inclusion in the Matlab System Identification Toolbox (Ljung 2000). However, in (Di Ruscio 1997) N4SID is criticized for finding the erroneous column space for the extended observability matrix[1] when colored noise enters the process, as opposed to DSR, CVA and PO-MOESP. Based on the results in Papers A – B this may very well be correct as it was experienced that N4SID always found a much higher model order than the DSR algorithm, without in general improving the model fit.

While e.g. PEM use an iterative search for optimal parameter values, subspace algorithm use linear algebra to find the parameters without iteration. Uncorrelated

[1]Estimation of the extended observability matrix is the first and common step in most subspace algorithms. From this matrix we can find the order n of the system and the A and C model matrices.

noise and inputs are a basic assumption in subspace algorithms, and thus used in a straight forward fashion these algorithms will not yield consistent estimates when closed loop data are used. For PEM, the use of closed loop data is in most cases un-problematic (Ljung 1999).

3.1.2 Empiric modeling of PM6

Empiric modeling of PM6 are covered in more detail in Papers A – B. In Paper A a high order mechanistic model is used as starting point for the empiric modeling, while in B both empiric modeling from experimentation on the high order mechanistic model and on the real process is carried out. The main results from empiric modeling of the real paper machine process are presented next.

The manipulated inputs u and the outputs y are

$$u = \begin{bmatrix} u_{TS} \\ u_F \\ u_{RA} \end{bmatrix}, \; y = \begin{bmatrix} y_{BW} \\ y_{PA} \\ y_{WC} \end{bmatrix}, \tag{3.6}$$

where the inputs u are the amount of *thick stock*, *filler* added at the outlet of the white water tank, and *retention aid* added at the outlet of the screens, and where the outputs y are the *basis weight* (weight per area), *paper ash* content (content of filler in the paper), and *wire tray consistency* in the recirculation flow from the wire to the white water tank. The basis weight and paper ash outputs are direct quality variables, while the wire tray consistency is an indirect quality variable having significant effect on variation in other short circulation variables (see Figure 2.2).

Identification of models with the subspace methods DSR and N4SID for model orders 1-30, and for various user defined parameters were carried out. The raw data observations were not equally spaced in time and a linear interpolation routine in Matlab was used for creating time series with five seconds sampling intervals, the sampling interval was approximately two seconds in the raw data. The identifications were repeated for data without pretreatment, data which were centered, and for data which were centered and scaled. The centering was carried out by subtracting the value of the first element in each input and output series[2], and the scaling was carried out by dividing each series with its standard deviation. Note that no particular consideration was given to the fact that the basis weight and paper ash measurements are updated less frequently than other variables.

A root mean square error (RMSE) criterion was used for comparing the identification and validation of the various models

$$RMSE_i = \sqrt{\frac{1}{N}\sum_{k=1}^{N} \left(\hat{y}_i(k|0) - y_i(k)\right)^2}, \tag{3.7}$$

where N is the number of observations, $y_i(k)$ is the measured output i at time k, and $\hat{y}_i(k|0)$ is the simulated output i at time k from the empiric model. The i's in the

[2] Centering may also be carried out e.g. by subtracting the mean of the series.

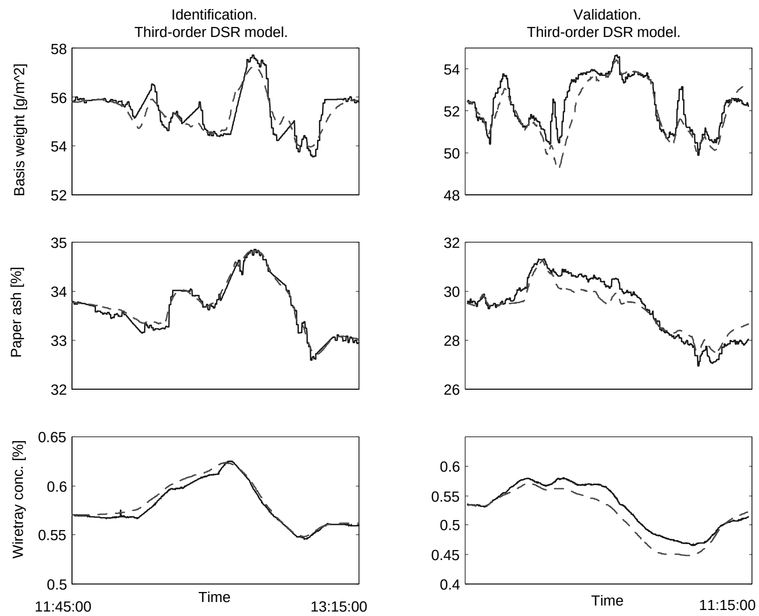

Figure 3.1: Real data (solid lines) and simulated data (dashed lines). Data set for identification collected at September 19. 2000, and data set for validation collected at October 27. 2000. Identification was carried out on centered data.

RMSE's are denoted as *weight* (basis weight), *ash* (paper ash content) or *conc.* (wire tray concentration). The simulated $\hat{y}_i$ are centered so that they have the same mean value as the measured responses y_i, before the RMSE's are calculated.

A third-order model with centered data was identified with the DSR method. Several higher order DSR models were identified, but non of these improved the validation RMSE values. The results from the identification and validation of this model is shown in Figure 3.1, and Table 3.1 gives the RMSE values.

With N4SID a fifth-order centered and scaled model was identified, in addition to several higher order models (11^{th} to 23^{rd} order models) with RMSE values comparable to those of the DSR models. The validation gave higher RMSE values for the fifth-order N4SID model than for the third-order DSR model. None of the higher order

Table 3.1: RMSE values for third-order DSR model.

	Identification	Validation
$\mathrm{RMSE}_{\mathrm{weight}}$	0.410	0.697
$\mathrm{RMSE}_{\mathrm{ash}}$	0.095	0.410
$\mathrm{RMSE}_{\mathrm{conc.}}$	0.0043	0.0173

N4SID models improved all three RMSE values at validation. The RMSE values for the basis weight were improved and the RMSE values for the wire tray consistency were poorer for all these models compared to the third-order DSR model.

All identified DSR and N4SID models were used as initial values for a corresponding PEM method. Some minor improvements on some of the DSR models were obtained at identification, however no validation improvements were found.

Individual[3] gains and time constants in the empiric models are far from the expected ones, the ones seen in step tests, or the ones in the mechanistic model implemented at PM6. This may be due to the experiments not being informative enough (Ljung 1999), and it suggests that quite extensive experimentation is needed in order to obtain a multivariable empiric model. It is however interesting to note that the validation results based on RMSE values seem to be quite good despite the poorly identified dynamics of the system.

3.2 Mechanistic modeling

3.2.1 Introduction

A mechanistic model is a model built from basic principles of physics, chemistry, biology, etc., by writing down conservation or balance equations. Obviously this requires extensive knowledge of the process to be modeled. In the literature one sometimes encounters terms like white-, and grey box modeling, see e.g. (Sohlberg 1998). White box models are mechanistic models based on complete knowledge of the process, i.e. where both equations governing the behavior and the associated parameters are known a priori. Obviously, such models are rarely found. A grey box model is a mechanistic model where the equations governing the behavior are assumed known, but parameter values need to be estimated using experimental or historical data. Throughout this thesis grey box models are included in mechanistic models.

There is a vast amount of literature on mechanistic modeling. Most sources deal with specific processes or process units, such as this thesis. However, studying a new process unit one often finds out that similar but not entirely the same units have been modeled, and often the models available are developed with another scope. A search for most of the known processes or process units in a data base will result in numerous hits.

In subsection 3.1.1 a procedure for parametric empiric modeling was outlined. Similar procedures for mechanistic modeling may also be found, e.g. in (Foss, Lohmann & Marquardt 1998), (Sohlberg 1998), and (Sælid 1984). The procedures for empiric and mechanistic modeling are similar to some extent, but with some exceptions:

- There are probably many more iterations and unstructured patterns of the iterations for mechanistic modeling compared to empiric modeling (Foss et al. 1998).

- Conceptual modeling enters as a step in the mechanistic modeling procedure. This step includes e.g. dividing the problem into several subproblems, making

[3] From **one** input to **one** output.

a list of relevant phenomena, and searching for literature (Foss et al. 1998), (Sælid 1984).

- Model simplifications enters as a step in the mechanistic modeling procedure (Sælid 1984).
- For a mechanistic model, the model structure and model order are chosen by formulating the physical laws and balances describing the process.

3.2.2 Mechanistic modeling of PM6

Mechanistic modeling of PM6 are covered in more detail in Papers A – C. In Papers A – B the model is not presented in detail, and neither is it fitted to real time data, nor is it validated with real time data. In Paper C the model is presented in detail, and it is also fitted to and validated with real time data. Thus, Paper C should be considered the main source of information about the mechanistic model developed for PM6. Probably, the most important reference used in the development of the PM6 model was (Shirt 1997):

> ... this work develops the first large scale dynamic simulation of a paper machine wet end which incorporates chemical phenomena (Shirt 1997, page 6).

More references can be found in Papers A – C. Despite the work carried out in (Shirt 1997), there seems to exist some resistance to mechanistic modeling of paper machines:

> The greatest problem here (concerning wet-end chemistry control. Authors note) is that it is not yet, nor is it likely to be, possible to generate a comprehensive physico-chemical model for the description of the adsorption, retention and other processes operative at the wet end of a multicomponent additive system. However, some success in control has been achieved with more empirical approaches (Roberts 1996*b*, page 8).

> The wet end of the paper machine is perhaps the most complex and important part of the paper making process, but can also be described as being one of the least understood sections as well. ... The physical modelling approach was thought to offer the best possible method for the papermachine [Humphrey 1986, Nicholson 1980]. However, the loss of material through the wire into the backwater was thought to be far too complex for purely physical modelling alone (Rooke 1999, page 31 and 104).

These claims are probably correct, and the objective of the mechanistic modeling of PM6 was not to make a detailed all-including model which in all aspects had the correct physical structure. The objective was to make a model of a limited part of PM6, which were suitable for model predictive control (MPC), captured the essential dynamic behavior of the process, and was applicable over a wide range of operating conditions. A similar thought is presented in (Scott 1996, page 136) which state that a comprehensive wet end control scheme will not work, and that the solution is to divide the overall process into subsystems and strive to reduce variability in each of them.

The deterministic model Some modifications have been introduced to the model detailed in Paper C, as compared to the model implemented at PM6. The most prominent modification is that a first order empiric model that was added to capture neglected and unknown dynamics in the process, has been removed.

The deterministic model was originally developed with several ordinary and partial differential equations. The model was then simplified, and eventually fitted to experimental and operational mill data. The implemented PM6 model consists of a third order nonlinear mechanistic model based on physical and chemical laws. The structure of the developed process model is

$$\begin{aligned} \dot{\bar{x}} &= \bar{f}(\bar{x}, \bar{u}, \bar{d}, \bar{\theta}) \\ \bar{y} &= \bar{g}(\bar{x}, \bar{u}, \bar{d}, \bar{\theta}), \end{aligned} \tag{3.8}$$

with $\bar{x} \in \mathbb{R}^n = \mathbb{R}^3$, $\bar{y} \in \mathbb{R}^m = \mathbb{R}^3$, $\bar{u} \in \mathbb{R}^r = \mathbb{R}^3$ and $\bar{d} \in \mathbb{R}^g = \mathbb{R}^4$. The bar above the variable names indicates that these are the variables in their original units and coordinate system. $\bar{\theta}$ consists of several model parameters, tuned to fit the model outputs to experimental and operational data.

The inputs and outputs are as shown in eq. 3.6. In the mechanistic model the states and measured disturbances are

$$\begin{aligned} \bar{x}^T &= \left[\bar{C}_{R,fil}, \quad \bar{C}_{WT,fil}, \quad \bar{C}_{D,fib}\right] \\ \bar{d}^T &= \left[\bar{C}_{\mathrm{TS,tot}}, \quad \bar{C}_{\mathrm{TS,fil}}, \quad \bar{v}, \quad \bar{f}\right], \end{aligned} \tag{3.9}$$

where $\bar{C}_{R,fil}$ is the concentration of filler in a *reject tank* in the hydrocyclones, $\bar{C}_{WT,fil}$ is the concentration of filler in the *white water tank*, and $\bar{C}_{D,fib}$ is the concentration of fiber in the *deculator*. The measured disturbances accounted for in the mechanistic model, are the total and filler thick stock concentrations $\bar{C}_{\mathrm{TS,tot}}$ and $\bar{C}_{\mathrm{TS,fil}}$, the paper machine velocity $\bar{v}$, and the paper moisture percentage $\bar{f}$.

Note that the total- and filler concentrations in the thick stock flow are called "measured disturbances", although they are not measured. A model of the thick stock area has been developed (Slora 2001), and implemented at PM6, providing *estimates* of total- and filler concentrations in the thick stock.

Parameter estimation in the deterministic model The model implemented at PM6 has many parameters. These parameters have physical interpretations and thus it should be possible to measure them (e.g. the volumes) or estimate them one by one from local measurements (e.g. measure the flows and concentrations in each stage of the hydrocyclones and calculate the associated parameters). This approach would require a very large and detailed model, probably not suitable for on-line use.

Table 3.2: Parameters estimated in PM6 model.

Name	**Description**	**Unit**
α_{filler}	conversion from total flow [l/s] to filler flow [kg/s]	kg/l
$\alpha_{\text{filler,Wire}}$	share of non-flocculated filler retained on the wire	–
$\alpha_{Cy1,\text{inject}}$	inject flow to first stage, relative to flow onto the wire	–
$\alpha_{Cy1,\text{filler}}$	filler accepted in first stage, relative to filler in inject flow	–
$\alpha_{Cy1,\text{fiber}}$	fiber accepted in first stage, relative to fiber in inject flow	–
$\alpha_{Cy2,\text{filler}}$	filler accepted in second stage, relative to filler in inject flow	–
$\alpha_{Cy2,\text{fiber}}$	fiber accepted in second stage, relative to fiber in inject flow	–
$\alpha_{\text{fiber,Wire}}$	share of non-flocculated fiber retained on the wire	–
$\theta_{T.S.\text{total}}$	bias on estimated thick stock total concentration	–
$\theta_{T.S.\text{filler}}$	bias on estimated thick stock filler share	–
k_{filler}	flocculation constant for filler	1/s
k_{fiber}	flocculation constant for fiber	1/s
$k_{\text{fiber-filler}}$	flocculation constant for filler	1/s
V_{Dr}	volume of deculator (right chamber)	m^3
V_R	volume of reject tank	m^3
V_{WT}	volume of white water tank	m^3
$x_{1,\text{initial}}$	initial value for filler concentration in reject tank	–
$x_{2,\text{initial}}$	initial value for filler concentration in white water tank	–
$x_{3,\text{initial}}$	initial value for fiber concentration in deculator	–

The model implemented at PM6 is a simple approximation of a complex process and the parameters in the model, although they have a physical interpretation, should not be measured and/or estimated one by one due to the poor input-output properties of the resulting model. Consider e.g. the deculator volume, which is important for characterizing the time constant for the sub-model between the thick stock and the basis weight. The real volume of the deculator is approximately $17\,\text{m}^3$ (right chamber), however in the model it is many times larger. The deculator volume in the model should be regarded as a lumped volume and not a single physical volume. The most important properties of the model are the input-output properties, i.e. the response on the outputs from changes in inputs. Thus, we want to estimate the parameters in the model so that these properties are good. In principle we would therefore like to tune the parameters so that the model outputs are equal to measured outputs. However, due to the large number of parameters in the model we set some parameters equal to values that seem reasonable, and estimate the rest. The parameters that we have chosen to estimate are shown in Table 3.2.

The function `lsqnonlin` in the Matlab Optimization toolbox (The MathWorks, Inc. 2000) is used for solving the minimization problem defined in eq. 3.1 – 3.3. The prediction errors ε are calculated by simulating the system, with only the initial conditions given, i.e. with $l = k + 1$ in eq. 3.2. In addition the optimization has been subject to the constraints

$$\theta_{\min} \leq \hat{\theta} \leq \theta_{\max}, \tag{3.10}$$

Traditional system identification (see e.g. (Ljung 1999)) is in most cases carried out using a one-step-ahead predictor, corresponding to $l = 1$, however in our case we wish to emphasize the need for a model with good long term prediction abilities. The reason for this is that the model will be used for model predictive control (MPC). Then, it seems natural to use the simulation approach in the parameter estimation algorithm.

The concept of scaling is very important for robust and rapid convergence to the optimal parameter values (Betts 2001). Here, we will point at two simple methods for scaling; scaling of parameters and scaling of the simulation error. Scaling of the parameters can be done by introducing

$$\theta = S \times \tilde{\theta}, \tag{3.11}$$

where $\tilde{\theta}$ is the scaled parameter vector, θ is the original non-scaled parameter vector, S is a scaling vector, and $\times$ is the Hadamard product (an element by element multiplication). The scaling vector S may be chosen so that the assumed scaled parameter values are close to unity. Consider e.g. the following assumed parameter vector

$$\theta = [10^{-5}, 10^{8}].$$

Choosing

$$S = [10^{-5}, 10^{8}],$$

gives the following scaled parameter vector

$$\tilde{\theta} = [1, 1].$$

Any constraints or bounds on the parameters must be scaled accordingly.

The simulation error is defined in equation 3.2 by setting $l = k + 1$. The basis weight is measured in $\mathrm{g/m^2}$ and has a value typically around $50\,\mathrm{g/m^2}$, paper ash is measured in % and has a value typically around 30%, and the wire tray concentration in measured in % has a value of approximately 0.6%. Based on this, it is easy to understand that the error for the wire tray concentration is very small compared to the other two errors, thus any model fitting routine would more or less ignore the wire tray concentration and concentrate on fitting the basis weight and paper ash. To compensate for this one may scale the simulation error or outputs, simply by multiplying with a weight. If all outputs are regarded equally important, one may weight them so that the outputs are approximately equal. For example, the wire tray could be multiplied by 50 to make it approximately equal to the paper ash. However, in our case we define the most important output to be the basis weight, the second most important output to be the paper ash, and the least important output is the wire tray concentration. This ranking of importance should thus also be reflected in the weighting of the outputs.

Validation and re-tuning of deterministic model Validation is the method of checking how good the model really is. One may find a model fitted almost perfectly to one data set, and totally failing to explain (failing to simulate outputs close to measured outputs) another data set. Many methods for validation exist, however if possible a proper validation should include testing of the model with a new data set. Using one half of the data set for model fitting and one half for validation is not an equally proper method, as slow varying disturbances and parameters , drifts, and trends, will be very hard to discover. Ideally, data sets spanning all operating conditions of the process should be used for validation, thus one would have a fair chance to find areas where the model is not functioning properly.

In subsection 3.1.1 a procedure for parametric empiric modeling is outlined, and in subsection 3.2.1 some similarities and differences between the empiric modeling procedure and a procedure for mechanistic modeling is pointed at. A similar procedure as the ones found in subsections 3.1.1 and 3.2.1 has been used for the PM6 model, although with some changes. Validating a model by comparing simulated and real outputs, is in general not enough when the model should be used for control. The individual responses from each input to each output are also very important. A procedure is presented next, which is used at PM6 and found to work well, for model fitting, validation and re-tuning of the model. The procedure is also pictorially presented in Figure 3.2.

1. Make model.

2. Collect several data sets, at least one for model fitting and one for validation. The data set used for model fitting should contain well excited data. The data set for validation must also to some extent be excited. The length of the data sets obviously depends on the process and size of the model. For the PM6 work, the data sets ranged from 2 hours to several days. It is usually not important wether the data are collected in open or closed loop since "*a directly applied prediction error method – applied as if any feedback did not exist – will work well and give optimal accuracy if the true system can be described within the chosen model structure*" (Ljung 1999, page 434). Check the data for outliers and that the units are correct, and also consider filtering of the data.

3. Set up tables of approximately expected gains and time constants from inputs and measured disturbances, to outputs. These gains and time constants could be found from discussions with process operators and engineers alone, but should be supported by step tests carried out on the process, if possible.

4. Choose initial parameter values and fit the model to the data. Several re-optimizations may be needed. For example if the optimal parameter values are very different from the initial values, then the optimal values should be used as initial values and optimized again (thus, a re-scaling is also carried out). Other reasons for re-optimizing may be to try other initial parameter values, or other parameter bounds. If reasonably good model fit is *not* obtained, changing the model equations may eventually be necessary.

5. Validate the model by comparing simulated and measured outputs, using a different data set than the one used for model fitting. If the result is not satisfactory one should probably return to point 4, and try different initial values or parameter bounds. Eventually one may need to change the model equations if reasonable validation results are not obtained.

Table 3.3: RMSE values for mechanistic PM6 models.

	Fitting M1	Fitting/re-tuning M2	Val. M1	Val. M2
Basis weight	0.21	0.25	1.00	0.71
Paper ash	0.24	0.40	0.87	1.20
Wire tray conc.	0.024	0.020	0.0496	0.042

Table 3.4: Gain ratios (M1/M2) for mechanistic PM6 models.

	Thick stock	Filler	Ret.aid
Basis weight	0.130 / 0.135	1.25 / 1.85	2.98 / 3.98
Paper ash	-0.023 / -0.022	1.63 / 2.40	1.66 / 5.10
Wire tray conc.	-0.00022 / -0.00057	0.081 / 0.11	-0.18 / -0.21

6. Simulate step tests on the fitted model, and compare the gains and time constants with the expected results as found in point 3. If the gains and time constants are reasonably close to the expected ones, the model fitting and validation is finished.

7. If the gains and time constants in point 6 are too far from the expected values, re-tune the model by changing parameter values that move the gains and time constants towards the expected ones. When reasonable gains and time constants are found, go to point 5 and compare simulated and measured outputs. Eventually one may need to change the model equations if reasonable gains and time constants are not found.

Figure 3.3 shows the validation result after fitting the model to an experimental data set, and Figure 3.4 shows the validation result after re-tuning to obtain expected gains and time constants. A comparison of the fitting and validation results are also given in Tables 3.3 and 3.4, based on the root mean square error values as defined in eq. 3.7 and the gains found in a specific operating point. In the tables we denote the fitted model by *M1*, and the fitted and re-tuned model by *M2*, i.e. the implemented model is denoted *M2*.

Comparing the RMSE values in Table 3.3, it seems that the basis weight fit became somewhat poorer after re-tuning the model, but the validation result improved significantly. The paper ash RMSE values became poorer after the re-tuning, while the wire tray total concentration RMSE values were improved. Studying the gain matrix in Table 3.4, it is seen that some gains changed dramatically, e.g. the gain between the thick stock and wire tray concentration more than doubled after the re-tuning. Similar results are found for the gains from the filler to the paper ash, and from the retention aid to the basis weight and paper ash.

Both models, M1 and M2, have been tested in MPC applications at PM6. It was observed that MPC with M1 resulted in e.g. poor grade changes due to the erroneous gains. These results are in accordance with the results from empiric modeling of PM6 in subsection 3.1.2. For the identified empiric model, the validation results were reasonably good, and it seemed that a model suitable for control was obtained.

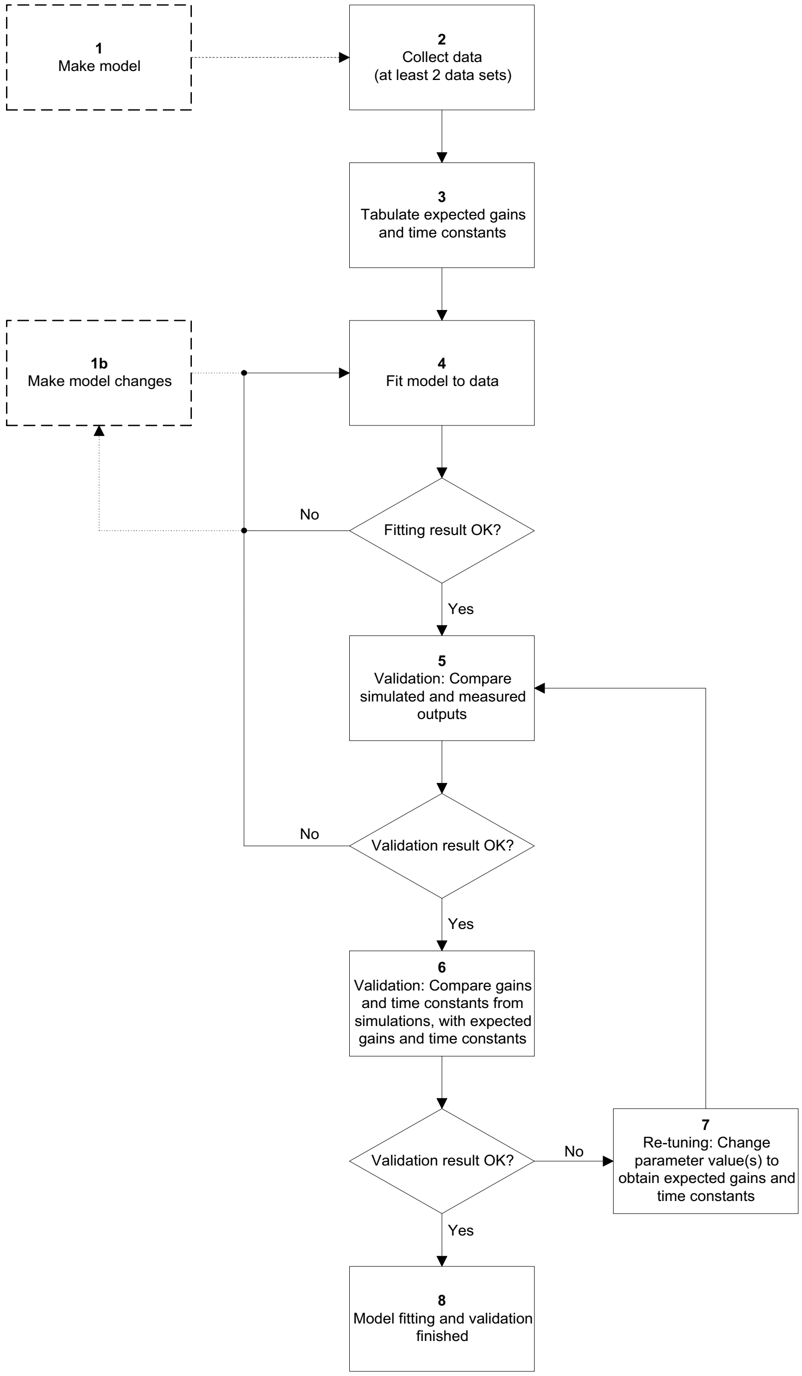

Figure 3.2: Procedure for model fitting and validation.

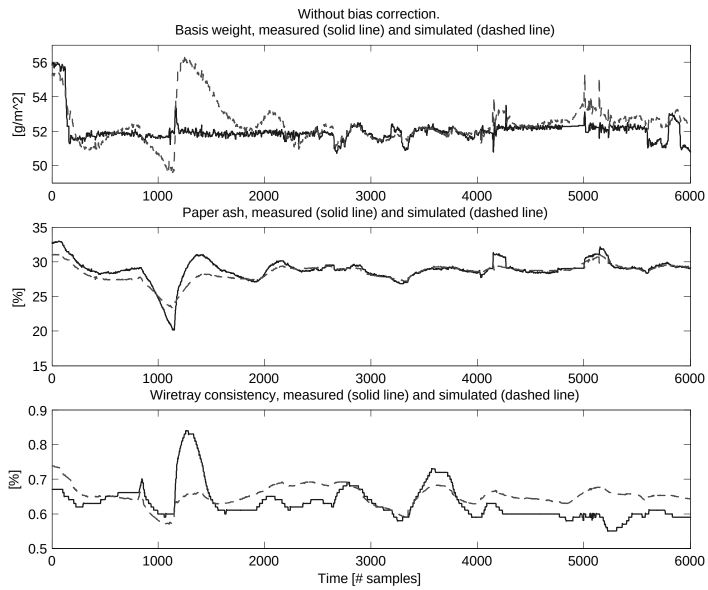

Figure 3.3: Validation of the model after fitting with `lsqnonlin`.

However studying the individual gains and time constants suggested that the model would probably work poorly for control applications due to large differences between model dynamics and dynamics in the real process.

Identification and tuning of stochastic model An augmented suboptimal Kalman filter is used at PM6 for estimating the states and some of the parameters in the paper machine model. As pointed out in (Muske & Badgwell 2002), only a limited number of parameters can be estimated on-line, thus the choice of which parameters or biases to estimate must be based on experience with the process and model. Three biases have been selected for on-line estimation in the paper machine model. The first two are biases on the estimated total- and filler thick stock consistencies (see eq. 3.9). These disturbances are estimated using a ballistic estimator (Slora 2001), and thus they are assumed to be good candidates for having time-varying biases. The third bias estimated on-line is for the total wire tray concentration, i.e. a bias in one of the outputs.

In theory, and in the true Kalman filter, the noise characteristics of the process should be found and used in the Kalman filter equations. However, these characteristics are hard, if not impossible, to find. Thus, one often aims for a suboptimal Kalman filter, where the noise characteristics are used as tuning parameters until satisfactory Kalman filter performance is obtained. Specifically, the tuning parameters are the augmented process noise covariance matrix, $\tilde{Q}_k$, and the measurement

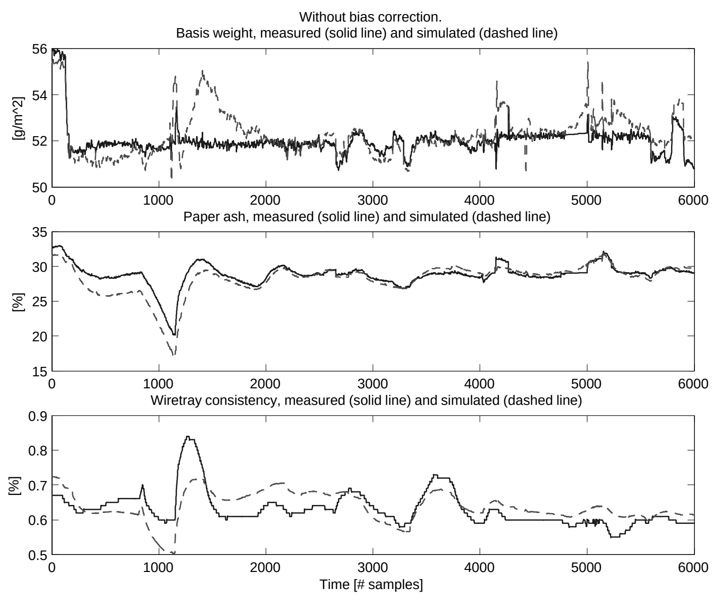

Figure 3.4: Validating the model after fitting with `lsqnonlin`, and re-tuning to obtain expected gains and time constants.

noise covariance matrix, R_k. Often, it is assumed that only diagonal elements are non-zero. Thus, for the paper machine model there are three diagonal elements in R_k (three outputs), and six diagonal elements in $\tilde{Q}_k$ (three states plus three estimated parameters).

When tuning and validating the (suboptimal) Kalman filter at PM6, a few facts and rules of thumb have been used, e.g.:

- The tuning and validation (with different data sets) should aim at
  - good tracking properties, i.e. the estimated outputs should follow the measured outputs to some extent;
  - good filtering properties, i.e. the estimated outputs should not track measurement noise;
  - a sound balance between the updating of states and updating of parameters, e.g. the parameters should not vary a lot while the states are more or less resting.
- It can be shown that it is the ratio of the various variances that determines the performance of the Kalman filter. Thus, one needs not be careful about finding realistic variance values.
- It is possible to estimate the variances, using a parameter estimation method. This is carried out for a constant gain Kalman filter (i.e. the individual variances are not estimated, but the Kalman filter gain matrix is estimated) in (Hauge & Lie 2002). The drawback with this method is that the Kalman filter will be rather aggressive, and some de-tuning procedure is needed (but it may give a good starting point).
- Start the tuning by finding approximate values for the various variances. The measurement variances can be approximately found by visually studying the random variations in the measurements. It is harder to find suitable starting values for the process noise variances and the parameter estimate variances. However, the expected state and parameter values will give good indications of reasonable starting values. Consider e.g. a concentration that is expected to have a value around 0.05 (5%). If one assumes that the noise entering this state is approximately 1% of the state value, we see that the variance will be a very small number. In the Kalman filter used at PM6, the measurement variances are much larger than the process and parameter variances (around 10^8 larger).
- In general, increasing the measurement variances leads to a slower updating of state estimates. The same result is obtained by decreasing the process variance. Thus, decreasing the process variance leads to a slower updating of state estimates.
- Since the parameters are augmented states, changing the parameter variances has much of the same effect as changing the state variances. Increasing the parameter variances leads to a faster updating of parameter estimates, thus

also leading to a faster elimination of estimation error (the difference between estimated outputs and measured outputs).

Refining versus lumping approach Studying Papers A – C, it is obvious that the mechanistic PM6 model has been developed basically in a *lumping approach*[4]: a large complex model was developed first, and simplifications were then carried out to establish a smaller and less complex model suitable for model based control. A *refining approach*[5] would include developing a coarse model, and then gradually refine the structure by introducing new elements.

In (Sohlberg 1998) a refining approach to modeling of a rinsing process within the steel industry can be followed closely. A basic model is developed first, consisting of only one unknown parameter. The model is fitted to data and refined in several stages before the final model, consisting of nine parameters, is achieved. The refining approach seems to be the preferred method amongst experienced modelers, although a certain mixture of the two approaches seems likely to occur in most projects (Foss et al. 1998). This mixing of approaches is also the case for the PM6 model. Even though the lumping approach is very pronounced, some elements of refining can be identified.

Two interesting questions are then: if a refining approach had been used for the PM6 model, (i) would the result be any different, and (ii) would the time spent on modeling be any different? (Sælid 1984, page 6) argues that if a too detailed model is developed, then much time and work is more or less wasted. This is probably correct for an experienced modeler having some knowledge about the process to be modeled, as (s)he will have an *a priori* feeling of the important phenomena and simplifications that can be carried out. For an unexperienced modeler, unfamiliar with the process (s)he is about to model, it will probably be much harder to identify sensible simplifying assumptions *a priori*. Consider e.g. the question of whether flocculation at PM6 takes place throughout the whole short circulation or only between the screens and the headbox. In the first model developed, the flocculation was assumed to take place in the whole short circulation, while the flocculation was constrained to take place only in the pipeline between the screens and the headbox in later versions of the model. This simplifying assumption was based on results from simulation, and sources such as (Shirt 1997), (Pelton 1984), (Koethe & Scott 1993), and (Gregory 1988). Next, consider a simpler example of how to model a pipeline. Assume for simplicity that no flocculation takes place within the pipeline, thus one expects that a very reliable model for the concentration in the pipeline is a partial differential equation (PDE)

$$\frac{\partial C}{\partial t} = -v\frac{\partial C}{\partial x}, \tag{3.12}$$

where v is the velocity of the mass inside the pipeline, and x is the variable corresponding to the direction along the pipeline. Using the method of lines (MOL) for discretization (Schiesser 1991), the choice of discretization level is a trade-off between

[4] Also called a bottom-up approach.
[5] Also called a top-down approach.

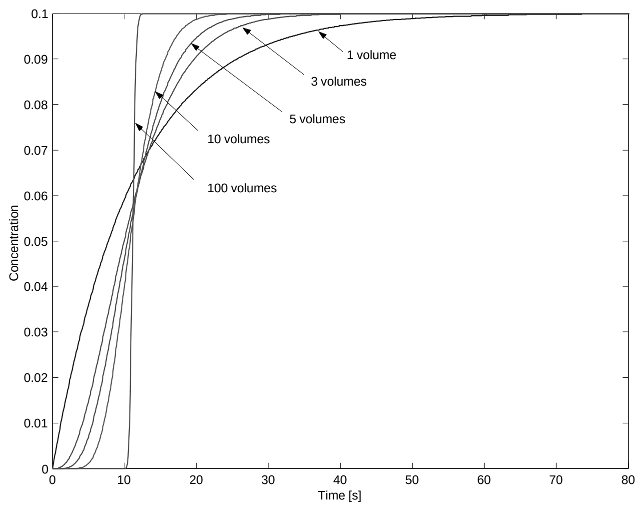

Figure 3.5: Step responses at the outlet of a pipeline (40 m length, $0.7\,\mathrm{m}^2$ cross sectional area, 2500 kg/ s mass flow). Discretization carried out with various numbers of ideally stirred volumes.

factors such as accuracy, complexity and numerical properties. With an increasing number of volumes, the model is more accurate but also more complex and the stiffness of the overall system is increased. The trade-off can be studied from the responses in Figure 3.5, where a step change (from 0 to 0.1) in the initial concentration is applied to the pipeline between the screens and the headbox. The pipeline is 40 m long, it has a cross section area of $0.7\,\mathrm{m}^2$ and a mass flow of 2500 kg/ s. A density of $\rho = 1000\,\mathrm{kg/m^3}$ is assumed. If the pipeline is a pure time delay then the step change would appear at the outlet at $t = L/(w/(A\rho)) = 11.2\,\mathrm{s}$, where L is the length of the pipeline. For the original PM6 model there were 100 pipelines included in the model. One advantage of using the lumping approach to modeling is then that the various choices of discretization can be easily studied using simulation, and one will have good control of which simplifications are negligible and not. In Paper A various simplified models are compared with a large basic model, showing that for the PM6 model all PDE's can be simplified to one ordinary differential equation (ODE) each without affecting the properties of the model to any large extent.

To sum up some thoughts and experiences: The refining approach is used by most experienced modelers in the field, however combined with some elements of the lumping approach. It is hard to find arguments supporting that a model will be better or worse using one approach or the other, however the time spent using the lumping approach may be longer than for the refining approach. For a novice in mechanistic modeling, the lumping approach may be more valuable in terms of gaining modeling experience.

3.2.3 Linearized PM6 state space model

In this subsection, a typical example of a linearized PM6 state space model is given. The structure of the linearized model is

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + Ed_k \\ y_k &= Cx_k + Du_k + Fd_k, \end{aligned} \tag{3.13}$$

where the sample time is 30 seconds, and the states, inputs, outputs, and measured disturbances are as described in eqs. 3.6 and 3.9. Typical model matrices are

$$\begin{aligned}
A &= \begin{bmatrix} 0.9702 & 0.3283 & 0 \\ 0.0018 & 0.9596 & -0.0197 \\ 0 & 0 & 0.8661 \end{bmatrix} \\
B &= \begin{bmatrix} 1.3 & 160.1 & 0.2 \\ 0.1 & 10.1 & -33.4 \\ 1.3 & 0 & -0.7 \end{bmatrix} \\
E &= \begin{bmatrix} 0.0247 & 0.0023 & 0 & 0 \\ 0.0016 & 0.0001 & 0 & 0 \\ 0.0134 & -0.0007 & 0 & 0 \end{bmatrix} \\
C &= \begin{bmatrix} 61 & 727 & 13,109 \\ 83 & 986 & -1692 \\ 3 & 34 & -32 \end{bmatrix} \\
D &= \begin{bmatrix} 0.0029 & 0.3544 & 5.3831 \\ 0.0040 & 0.4815 & 7.1769 \\ 0.0001 & 0.0166 & -0.0554 \end{bmatrix} \\
F &= \begin{bmatrix} 54.5613 & 5.1415 & -1.9777 & 51.0179 \\ 74.1090 & 6.9836 & 0 & -30.6923 \\ 2.5519 & 0.2405 & 0 & 0 \end{bmatrix}
\end{aligned} \tag{3.14}$$

3.3 Mechanistic versus empiric models

Table 3.5 summarizes some general properties of mechanistic and empiric models, although exceptions can easily be found.

The perhaps strongest argument for using an empiric model is that the time for building such a model is much lower than for a mechanistic model. In (Foss et al. 1998) it is indicated that the development cost for an empiric model is about 1/10 compared to a mechanistic model. This was indicated by a person experienced with mechanistic modeling, and for the paper machine modeling in Papers A – C the ratio is probably closer to 1/100. Another positive feature of empiric models are that they often have a simple structure (linear and time invariant) which leads to quick and easy simulation, analysis, and design of control algorithms. If one has access to experimental data,

Table 3.5: Mechanistic versus empiric models. Partly reproduced from Støle-Hansen 1998, and Walter & Pronzato 1997.

Properties	**Mechanistic**	**Empiric**
Utilize physical knowledge and insight	yes	no
The parameters have known range	yes	no
Number of unknown parameters	low	high
Time needed to develop a model	high	low
Resources needed to maintain a model	low	high
Easy to use for complex/unknown processes	no	yes
Amount of data needed	low	high
Applicability to control and training	yes	yes
Applicability to design	yes	no
Extrapolation properties	good*	bad
Increases process knowledge	yes	no
Complex	yes (non-linear)	no (often linear)
Simulation	long/difficult	quick/easy
Possible roll-out of model	yes	no

*if structure is correct.

and the operating region of the process is only moderately nonlinear, then it seems reasonable to first try an empiric model.

The strength of a mechanistic model lies in its ability to capture known nonlinear phenomena and thereby having extraordinary extrapolating properties, and the possible reuse of the model on similar processes. This and other features are emphasized in the following quotation:

> ..., a model based on first principles can operate in a larger domain than a black-box model. A model based on first principles will in general contain fewer parameters and will therefore be more parsimonious. From the parsimony principle we know that the best model is the simplest model that adequately describes the process, since overparameterization will in general lead to poor generalization. A consequence of fewer parameters, a model based on first principles will need fewer experiments to be identified. On the other hand, a black-box structure is easier to develop. ... To identify our model (a mechanistic model. Authors note) we have only used history data from the plant. (Hillestad & Andersen 1994, page 42 and 45)

Consider the paper machine model implemented at PM6. This model has 19 parameters, including two biases and three initial ODE values, which is tuned to fit the model to data. The model has three inputs, three outputs, three states, and four measured disturbances. A linear (empiric) state space model of the same dimension would consist of 63 parameters, including direct input to output matrix and three initial ODE values. An empiric transfer matrix model would consist of *minimum* 42 parameters, corresponding to pure first order elements, i.e. one parameter for the time constant, and one for the gain, in each element. If a step response model or impulse response model is used, the number of parameters would increase even more. In addition, the empiric models mentioned here have a limited operating range and must either be adaptive or a set of models is needed. In (Kosonen et al. 2002) an approach where a set of adaptive empiric models are used to cover the operating region of the paper machine is described.

A point made by (Ogunnaike & Wright 1997, page 49), is that mechanistic modeling results in a small number of parameters that can intuitively be understood, thus reducing long term support cost. Industrial processes do not remain static and it is likely that the model, whether empiric or mechanistic, will degrade with time. Another point, which is often neglected in the literature, is that the un-manipulatable nature of most measured disturbances makes it impossible to model their effect on the model outputs empirically. The empiric PM6 model developed in subsection 3.1.2 consists of none measured disturbances. Submodels from measured disturbances to model outputs can in some cases be identified from experimental data, however in most cases the data will not be informative enough and physical knowledge and insight must be used. For example the thick stock total consistency could be incorporated in the model by assuming that it affected the outputs similarly to the thick stock input.

Chapter 4

Model Predictive Control

4.1 Introduction

Readers not familiar with model predictive control (MPC) may consult one of the many texts on the subject. Introductory textbooks on MPC are e.g. (Maciejowski 2002) focusing on MPC with state space models, and (Camacho & Bordons 1999) focusing on MPC with transfer function models. A tutorial is given in (Rawlings 2000), and survey papers focusing on both theory and practice are e.g. (Garcia, Prett & Morari 1989), (Mayne, Rawlings, Rao & Scokaert 2000), (Qin & Badgwell 1997), and (Qin & Badgwell 1998).

In model predictive control (MPC) one calculates optimal inputs in a receding horizon fashion. The inputs at time k are calculated by minimizing a criterion aiming at keeping control errors small, the inputs close to some preferred values, the input changes small, and the inputs, outputs, and input changes within some predefined bounds. A typical mathematical formulation of the criterion may be

$$\min_{\mathcal{U}_k} J_k = \min_{\mathcal{U}_k} \sum_{j=0}^{\infty} \left[e_{k+j}^T Q e_{k+j} + \tilde{u}_{k+j}^T R \tilde{u}_{k+j} + \Delta u_{k+j}^T S \Delta u_{k+j} \right], \tag{4.1}$$

constrained by the definitions

$$\begin{aligned} e_{k+j} &= y_{k+j} - r_{k+j}^y \\ \tilde{u}_{k+j} &= u_{k+j} - r_{k+j}^u \\ \Delta u_{k+j} &= u_{k+j} - u_{k+j-1}, \end{aligned} \tag{4.2}$$

the model of the process, e.g.

$$\begin{aligned} x_{k+1+j} &= f(x_{k+j}, u_{k+j}, d_{k+j}) \\ y_{k+j} &= g(x_{k+j}, u_{k+j}, d_{k+j}), \end{aligned} \tag{4.3}$$

and the bounds

$$\begin{aligned} u_{k+j}^{\min} &\leq u_{k+j} \leq u_{k+j}^{\max} \\ y_{k+j}^{\min} &\leq y_{k+j} \leq y_{k+j}^{\max} \\ \Delta u_{k+j}^{\min} &\leq \Delta u_{k+j} \leq \Delta u_{k+j}^{\max}, \end{aligned} \tag{4.4}$$

where y and r^y are the outputs and output targets, u and r^u are the inputs and input targets, x are the states, d are the disturbances acting on the system, and Q, R, and S are weighting matrices. The input sequence $\mathcal{U}_k$ covers the inputs from the present time and N steps into the future, however only the first input is applied to the process. At the next time instant, the computation is carried out again with the same length N of the horizon, giving another input to apply to the process. Thus, the inputs are computed in a receding horizon fashion, and MPC is occasionally called receding horizon (optimal) control.

The basic MPC principle is shown in Figure 4.1. Here, the principle is illustrated using only one input and one output (the basis weight of a paper machine), although a major advantage of MPC is its ability to handle multivariable systems in a straightforward fashion. In the figure, the reference changes 15 minutes into the future, giving the process operators time to evaluate the controller action. Even though this functionality is available and described in many introductory texts on MPC (Camacho & Bordons 1999) (Maciejowski 2002), most commercial MPC's have not implemented this facility. Instead, the change takes place immediately, or a trajectory is calculated from the present setpoint to the new setpoint.

Linear model predictive control, i.e. MPC with linear models, is the only advanced control method used to any extent by the industry. The main reasons for its success are probably

- Intuitive and attractive concept.
- Constraints are handled in an elegant fashion.
- Compensates for dead time.
- Handles measured disturbances by feed forward control.
- Handles coupled multivariable systems with elegancy.
- Short payback time is reported, e.g. 3 months in (Bassett & Van Wijck 1999).
- Commercial MPC software packages are available.
- Linear empiric models can be developed efficiently, with or without commercial software.

Nonlinear model predictive control, with mechanistic models, is not reported used in many industrial applications. The reason for this is probably that the modeling procedure is more expensive and time consuming, and that many of the larger vendors only support linear models in their MPC's. However, there are cases where it seems reasonable to use nonlinear MPC with a mechanistic model, e.g. when:

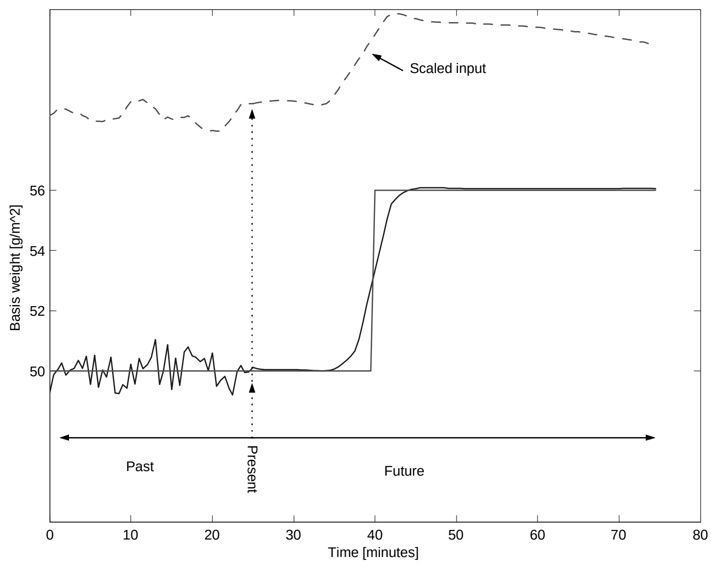

Figure 4.1: Basic MPC principle.

- The process is nonlinear, with wide operating range or several grades.
- Limited experimentation can be carried out on the process. Less experimentation is needed for fitting a mechanistic model compared to an empiric model, e.g. (Hillestad & Andersen 1994) reports that their mechanistic model is identified purely from historical data.
- There are a number of similar processes or process units, which the controller is sought applied to.

Algorithm for MPC with mechanistic model Here, an algorithm for MPC with a mechanistic model is suggested. The algorithm is detailed in Paper F.

The basic idea of the algorithm is that the nonlinear mechanistic model can be approximated by a linear model which is updated at each sample, thus using successive linearization, extended Kalman filter, and a linear MPC framework. Similar approaches are also suggested in (Lee & Ricker 1994), although with a finite horizon criterion, and (Gattu & Zafiriou 1992), with computation of the steady state Kalman gain at each sample.

At time k we have available the process model (eq. 3.8) in its discrete version

$$\begin{aligned} \bar{x}_{k+1} &= f(\bar{x}_k, \bar{u}_k, \bar{d}_k, \bar{\theta}_k) \\ \bar{y}_k &= g(\bar{x}_k, \bar{u}_k, \bar{d}_k, \bar{\theta}_k), \end{aligned} \tag{4.5}$$

as well as the following past measurements and estimates

$$\left.\begin{array}{l}\bar{u}_{k-i}\\ \bar{y}_{k-i}\\ \bar{d}_{k-i}\\ \widehat{\bar{x}}_{k-i+1}\end{array}\right\}, \forall i = 1, 2, 3..., \tag{4.6}$$

where $\widehat{\bar{x}}$ is an estimated state vector. The following step by step algorithm for controlling the process is suggested, assuming the present time to be k.

1. Linearization of model based on conditions at time $k-1$.

   The linearization is based on the most up-to-date information about the process, i.e. the variable values at time $k-1$. Note that we have no information about $\bar{u}_k$ yet, so we can not linearize based on variable values at time k. The resulting model is

$$\begin{aligned}\bar{\bar{x}}_{k+1} &= A_k\bar{\bar{x}}_k + B_k\bar{\bar{u}}_k + E_k\bar{\bar{d}}_k \\ \bar{\bar{y}}_k &= C_k\bar{\bar{x}}_k + D_k\bar{\bar{u}}_k + F_k\bar{\bar{d}}_k.\end{aligned} \tag{4.7}$$

2. Obtain current measured disturbances and future setpoints and disturbances.

   The measured disturbances obtained from the process are $\bar{d}_k$. The future disturbances and references are

$$\begin{aligned}&\bar{r}_{k+j},\ j = 0, ..., N-1 \\ &\bar{d}_{k+j},\ j = 0, ..., N-1,\end{aligned} \tag{4.8}$$

   which must be provided by the process operators or simply taken as an extension of the present values into the future.

3. Shift variables, i.e. change variable coordinates, corresponding to the linearized model.

   The references, disturbances, and constraints will be used with the linearized model in eq. 4.7 for calculation of target or steady state values. The references, disturbances, and constraints must then be shifted along with the model so that all variables have compatible origins before the calculation of target values.

4. Calculate steady state values.

   The calculation of steady state values is carried out for several reasons. The steady state values are used as targets in the optimization criterion. One could use e.g. reference values directly as targets in the criterion. However, the calculation of steady state values is a way of ensuring that the targets are feasible. In addition, by calculating steady state values one has the opportunity to add e.g. an economic type criterion if there are additional degrees of freedom. Finally, for the special case of an infinite horizon criterion with possibility of changing future references and measured disturbances, we need the steady state values at the end of the horizon in order to shift the origin of the model.

5. Shift the origin of the model to the steady state values at time $k+N-1$.

   The model origin is shifted so that the variables in the criterion converge exponentially to a zero steady state, thus avoiding an infinite value of the criterion in eq. 4.1. The resulting model is

$$\begin{aligned} x_{k+1} &= A_k x_k + B_k u_k + E_k d_k \\ y_k &= C_k x_k + D_k u_k + F_k d_k. \end{aligned} \tag{4.9}$$

6. Shift measured and estimated variables.

   The variables must be shifted along with the model so that they have the same origin.

7. Update MPC matrices and vectors.

   The matrices and vectors in the MPC formulation that contain time variant variables, such as linear model matrices, input variables, estimated states, etc., must be updated.

8. Optimization.

   An optimization algorithm is used to calculate optimal inputs.

9. Apply $\bar{u}_k$ to the process.

   Note that only the first input is used.

10. Obtain $\bar{y}_k$ from the process.

11. Estimate $\widehat{\bar{x}}_{k+1}$.

    Unless all states are measured, we need to estimate them (or some of them). Typically an extended Kalman filter is used for this purpose.

12. Set $k := k+1$ and go to step 1

Note that variables in original units, i.e. unscaled and unshifted, are denoted by a bar above the variable, e.g. $\bar{x}$ and $\bar{u}$. Variables in the linearized model, i.e. variables that have origin corresponding to the center of linearization are denoted by a double bar above the variable, e.g. $\bar{\bar{x}}$ and $\bar{\bar{u}}$. Finally, variables shifted first by linearization and then by the steady state values at time $k+N-1$ are shown as e.g. x and u.

Computational efficiency Consider the criterion and constraints in eqs. 4.1 – 4.4. The choice of unknown variables are here given as the future input sequence $\mathcal{U}_k$. By extensive manipulation (see Paper F) the criterion and constraints can be formulated as the following quadratic programming (QP) problem

$$\min_{\mathcal{U}_k} J_k = \min_{\mathcal{U}_k} \left(\frac{1}{2} \mathcal{U}_k^T H_k \mathcal{U}_k + c_k^T \mathcal{U}_k \right), \tag{4.10}$$

subject to

$$b_{L,k} \leq \begin{bmatrix} \mathcal{U}_k \\ \bar{A}_k \mathcal{U}_k \end{bmatrix} \leq b_{U,k}, \tag{4.11}$$

which can be solved by commercial QP software. This choice of unknowns in the optimization criterion is by no means the only one, however in Paper E it is shown that reducing the number of variables to a minimum often is beneficial for the computation time. It is also shown that the efficiency of commercially available QP solvers varies quite much. Consider a simulated case using the mechanistic model of PM6 and the MPC algorithm above. The number of variables are down to a minimum, i.e. only future input variables are computed, and we simulate 100 samples (50 minutes), with a rather short horizon $N = 20$ samples. After 20 samples a step change in the reference values occur. The change is known to the MPC from the start of the simulation. One instance of outputs from such a simulation are shown in Figure 4.2, and the computation time using `qpopt` (Holmström 2001) and `quadprog` (The MathWorks, Inc. 2000) are shown in Figures 4.3 - 4.4 respectively. It is clear that `qpopt` is superior to `quadprog` when it comes to computing efficiency. No difference in computing accuracy has been found between the two solvers in this study. Some statistics from the two simulations are:

Solver	mean comp. time	1.opt. comp. time	mean(2:end) comp. time
`qpopt`	0.013 s	0.11 s	0.012 s
`quadprog`	0.616 s	14.52 s	0.476 s

Here, “mean comp. time” is the average computation time for all 100 samples, “1.opt. comp. time” is the computation time for the first optimization carried out, and “mean(2:end) comp. time” is the average computation time for all 100 samples except for the first.

4.2 Model predictive control at PM6

Model predictive control at PM6 is covered in more detail in Paper F.

Motivation for multivariable model based control Magazine paper is characterized by its glossy appearance due to a high content of filler in the paper. The finished magazine paper typically consists of 65% fiber, 30% filler, and 5% water. The main difference between magazine paper and e.g. newsprint is the high content of filler. For newsprint, the amount of filler is typically 0-10%. Due to the high filler content in magazine paper, the couplings between important input and output variables are relatively strong. The project “Stabilization of the wet end at PM6” was initiated in 1999 based on the experience of strong couplings and oscillating behavior in the process. A key goal was to reduce variation in certain variables, such as consistencies in the short circulation, basis weight, filler content, and more. Based on experience and reported results from competitive mills (e.g. (McQuillin & Huizinga 1995), and (Lang et al. 1998)), it was decided to develop a model of the

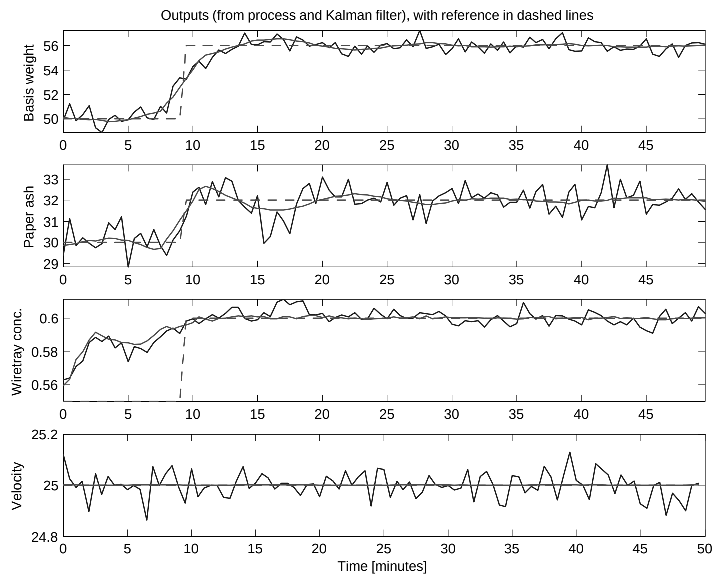

Figure 4.2: Outputs (measured, estimated and reference) after simulation of 100 samples, with horizon $N = 20$. A change in reference values occurs after 10 minutes.

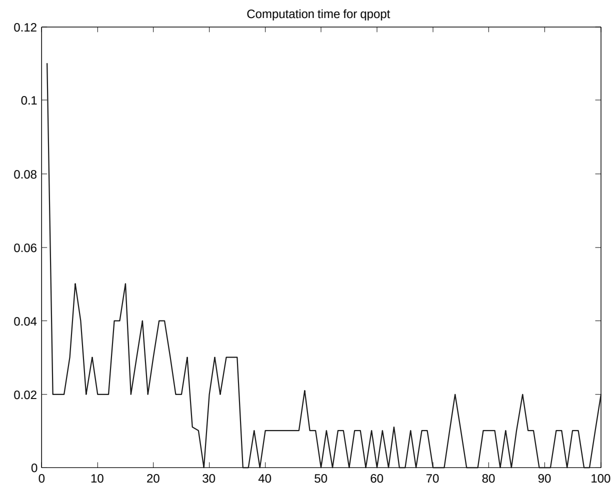

Figure 4.3: Optimization time using qpopt. Simulation carried out with 100 samples, and with horizon $N = 20$. A change in reference values occurs after 10 minutes (20 samples).

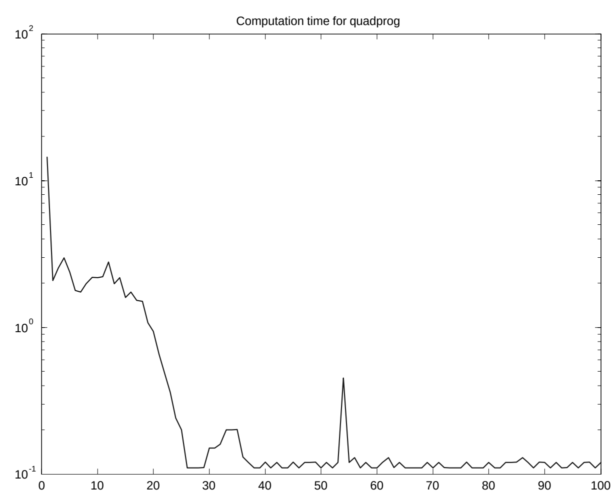

Figure 4.4: Optimization time using quadprog. Simulation carried out with 100 samples, and with horizon $N = 20$. A change in reference values occurs after 10 minutes (20 samples).

process and utilize this in a model predictive controller. Input, output, and measured disturbance variables were selected as shown in eqs. 3.6 and 3.9.

Before the project started, single loop controllers and manual control were used. Grade changes were carried out manually or partly manually by the operators: the setpoints were changed a number of times before they were equal to the new grade. During start ups, the controllers were kept in manual mode until the measurements were close to the desired specifications. In addition, during sheet breaks the basis weight and paper ash measurements were lost and the inputs controlling these variables were set equal to the values that they had prior to the sheet break. The controllers were kept in manual mode until the paper was back on the reel. Thus, it was also a key goal in the project to be able to have the controllers in automatic mode during grade changes, sheet breaks, and start ups.

APIS MPC A commercial MPC developed by Prediktor AS (www.prediktor.no), was chosen by Norske Skog for implementation. The choice of MPC was based on (i) cost, and (ii) the ability to add and develop certain features that were important. Special features that were important were the abilities to

- utilize the non-linear model;
- specify future reference changes. This means that the process operators can specify a setpoint change some time into the future, see how the controller will respond, and let the controller do the grade change if they are satisfied with the response. In many systems, the setpoint is constant into the future, so once a change in setpoint is made, the controller will respond immediately, giving the operators no time to consider how wise the response is;
- make an interface suitable for gaining operator acceptance of the MPC;
- use the MPC during grade changes, sheet breaks, and start ups.

The commercial MPC is part of a software package named Apis (Advanced Process Improvement System), which also consists of a Kalman filter, subspace system identification, and more. The Apis MPC was intended for linear models, based on the infinite horizon objective function presented in (Muske & Rawlings 1993). For the predictive controller implemented at PM6, several extensions were made to the original MPC, such as

- on-line linearization at each sample;
- on-line estimation of key model parameters/biases;
- future setpoint changes, i.e. the process operators can submit new setpoints to the controller some time before the actual grade change;
- addition of a direct input to output term;
- inclusion of measured disturbances.

The use of MPC, a nonlinear model, extended Kalman filter, and linearization at each sample, has also been suggested by (Lee & Ricker 1994), although with a finite horizon criterion. Similarly, (Gattu & Zafiriou 1992) proposed an algorithm for nonlinear MPC, with linearization at each sample, but with computation of the steady state Kalman gain at each sample.

Implementation and interface The MPC was installed at PM6 in March 2002. During the first two months, the MPC, the Kalman filter and the model were continuously tuned, retuned, and validated in open and closed loop. Some structural changes were also made during these months. From May 2002, the MPC has been in operation more or less continuously. The process operators still have the original "pre-MPC era" control configuration available, but the MPC has been the preferred choice from the beginning. Furthermore, the operators have been very active in making suggestions for improvements and new features in the system. Some of these suggestions are implemented, and others are being considered for implementation.

In addition to discussing with and involving the operators in the project from the beginning, it seems that the MPC interface has been very important for the positive operator attitude. Figure 4.5 shows part of the MPC interface at PM6. The upper row in the figure shows the basis weight, setpoint for basis weight, and the flow of thick stock. The middle row shows the paper ash, setpoint for paper ash, and the flow of filler added to the short circulation. The lower row shows the total concentration in the wire tray, the corresponding setpoint, and the flow of retention aid added to the short circulation. The interface and pairing of inputs and outputs are based on the pre-MPC era control configuration, basically because this is how the operators and engineers at PM6 are used to see it. The vertical dashed line in the middle of each row is the current time. When Figure 4.5 was captured, the paper machine was in the middle of a grade change, and studying the figure carefully, one may see the setpoints change at the current time. The setpoints for the new grade were submitted to the MPC some time before the grade change, so at the time of the grade change the outputs are actually half way to the new setpoints. In terms of gaining operator acceptance for the MPC, this feature of previewing the action taken by the controller has been very helpful. The operators can specify a grade change e.g. half an hour into the future, and see how the MPC will achieve the change: how the inputs will be manipulated to reach the new setpoints.

Reduction of variation An important objective with the MPC was to reduce variation in consistencies, basis weigh, paper ash, paper moisture, and more. Figure 4.6 shows an example with the wire tray concentration and the paper ash. The bottom line indicates whether the MPC is on (at 1) or off (at 0). When the controller is off, the original control configuration is used. The MPC provides a distinct effect of reduced variation in these two outputs.

The main objective of the project "Stabilization of the wet end at PM6" was to increase the total efficiency by 0.47%. This is an objective that is hard to measure, due to many factors affecting the total efficiency. Thus, several sub-goals were defined which were assumed easier to measure and validate. The sub-goals, and results,

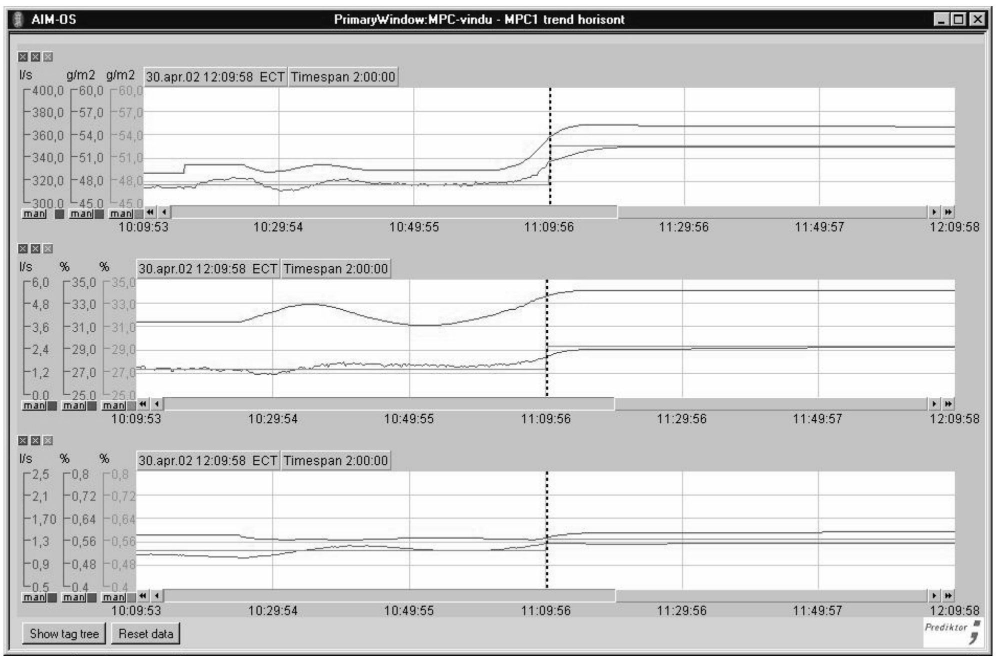

Figure 4.5: Part of the MPC interface at PM6.

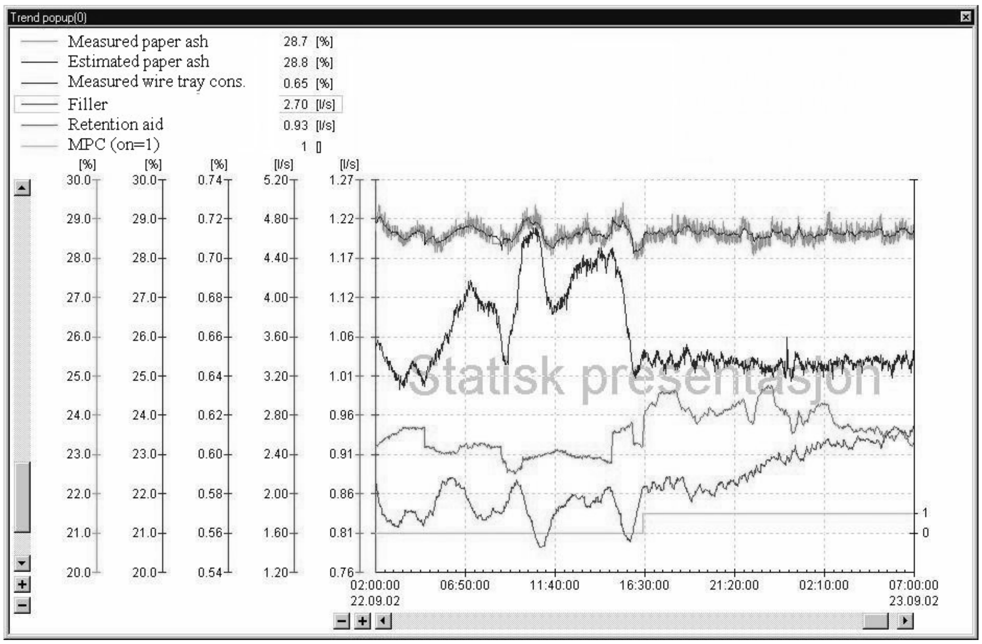

Figure 4.6: Wire tray concentration and paper ash, with (bottom line is 1) and without (bottom line is 0) MPC. From top to bottom the following variables are shown: Measured and estimated paper ash (overlapping), wire tray total concentration, retention aid, filler, and MPC on/off indication.

concerning reduced variability are:

Variable	**Sub-goal (red. std. dev.)**	**Result**
Total cons. in the wire tray	60%	Achieved
Filler cons. in the wire tray	50%	Achieved
Total cons. in the headbox	50%	Achieved
Filler cons. in the headbox	35%	Achieved
Basis weight	20%	Not achieved
Paper ash	20%	Achieved
Paper moisture	20%	Achieved

These sub-goals were defined in 1999 when the project was initiated. In 2001 a new scanning device for measuring e.g. basis weight and paper ash was installed at PM6. This significantly improved the control of the basis weight using the "old" controllers. The results in the table above are calculated with the measurement devices as of 2002, comparing the old control configuration with the MPC control configuration. Exact numbers for the reduction in standard deviation are not given, as they vary from day to day, and from operator to operator.

Other benefits of MPC In addition to reducing the variation in key paper machine variables, several other benefits are obtained using MPC. Some of these benefits arise from utilizing the developed model, not only for control purposes, but also as a replacement for measurements when these are not available or not trustworthy:

- Previously, grade changes were carried out manually or partly manually; the setpoints were changed a number of times before they were equal to the new grade. With a mechanistic model, applicable over a wide range of operating conditions, the grade changes are carried out using the MPC (see Figure 4.5). This has resulted in faster grade changes and operator independent grade changes. During larger grade changes, the use of MPC results in less off-spec paper being produced during the change. Using one mechanistic model, the grade change is handled in a straight forward fashion, as there is no need to switch between various local models.

- The basis weight and paper ash outputs can not be measured during sheet breaks. Previously, during sheet breaks the flow of thick stock and filler were frozen at the value they had immediately prior to the break. Usually the sheet breaks last less than half an hour, and the output variables are not far from target values when the paper is back on the reel. However, occasionally the sheet breaks last longer periods and there may be e.g. velocity changes during the break, leading to off-spec paper being produced for a period following the break. Another frequently experienced problem are large measurement errors immediately after a sheet break. With the MPC, the Kalman filter estimates the basis weight and paper ash during sheet breaks, and these estimates are used in the MPC as if no break had taken place. Thus, when the paper is back on the reel, the outputs are close to their setpoints.

- Previously, the controllers were not set to automatic mode before the outputs were close to the setpoints, following a start up. With a model based controller using a mechanistic model with a wide operating range, the MPC is set to automatic mode early during start ups. This results in faster start ups, and less off-spec paper being produced.
- Occasionally a special filler is added to the stock, to increase the brightness of the paper. During these periods the consistency measurements are not trustworthy as they are based on optical measurement methods. This problem is solved within the MPC / Kalman filter framework by neglecting the updates of the consistency estimate, relying on the estimate alone. For each output, there is an option within the MPC to neglect the updating of states based on this output. This is done based on experience with periods of poor measurements, even when only standard filler is used.
- The Kalman filter estimates are used in the MPC instead of the measurements. This leads to smoother controller action, and eliminates the need for additional filtering.
- The model is augmented so that some key parameters/biases are updated automatically. This reduces the need for model maintenance off-line. However, should there be larger changes in the process, such as if the white water tank is removed, or a new retention aid is used, then it will probably be necessary to re-tune the model and controller.

Further MPC refinements Based on inputs from amongst others the process operators, some refinements have been carried out. One of these are the inclusion of the paper machine velocity as both an input and an output in the model formulation. A change in paper machine velocity has a direct and distinct effect on the basis weight. Previously, the velocity was implemented as a measured disturbance in the MPC. Thus, when a change in the velocity occurred this lead to a deviation in the basis weight which it took some time to compensate for. Now, the process operators can submit a new velocity and the time for the velocity change to the MPC. The MPC will then know about this change in advance and take corrective action to prevent disturbance in the other outputs. This is illustrated in a simulated example in Figures 4.7-4.8. The velocity change was submitted to the MPC at the start of the simulation, and due to constraints on the allowed change per sample, the velocity approach the new setpoint in a ramp. The other outputs are more or less unaffected because the controller starts to compensate before the velocity change has actually happened.

In Figures 4.9 – 4.11 a sequence of screen dumps from part of the operator interface is shown. The sequence shows a grade change at October 7th, 2002, and it shows the paper machine velocity included in the interface in the fourth row.

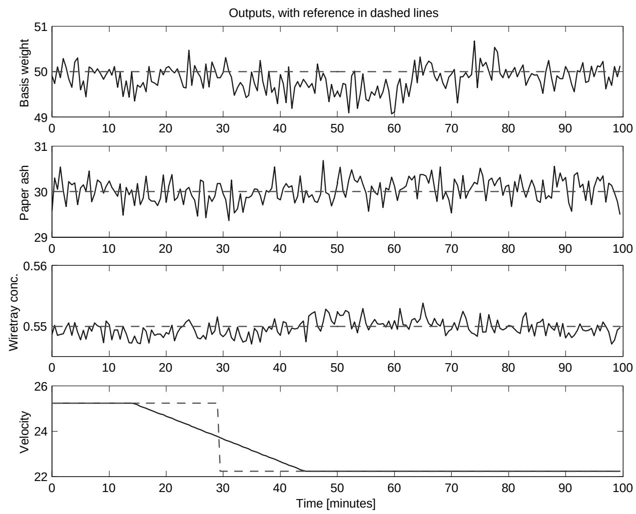

Figure 4.7: Outputs during simulation of velocity change from 25 m/ s to 22 m/ s.

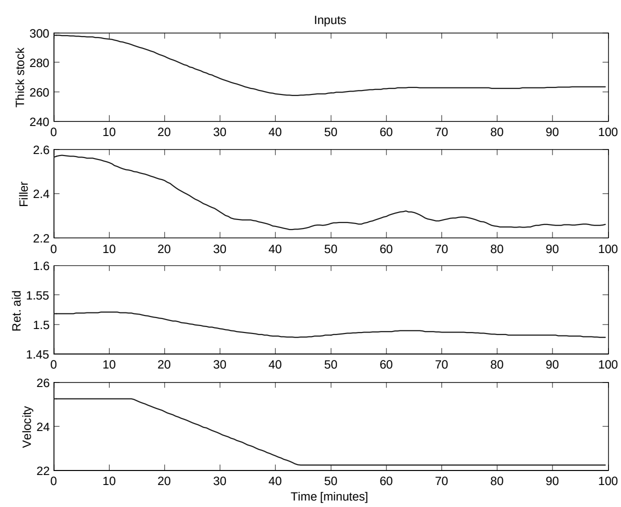

Figure 4.8: Inputs during simulation of velocity change from 25 m/ s to 22 m/ s.

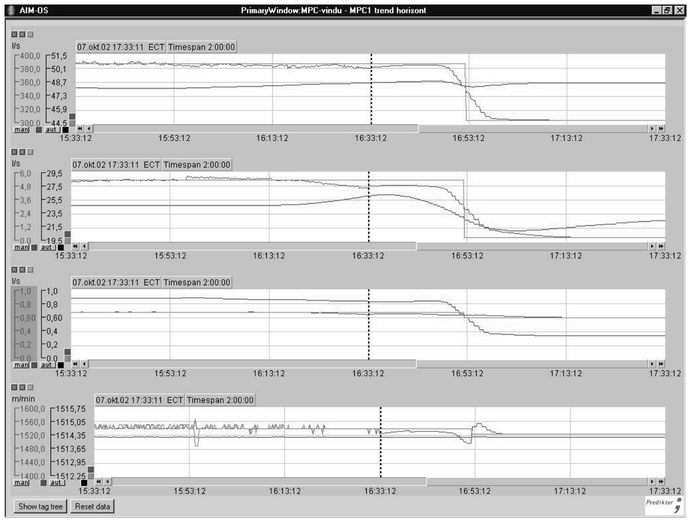

Figure 4.9: New setpoints for grade change at October 7th, 2002, have just been submitted.

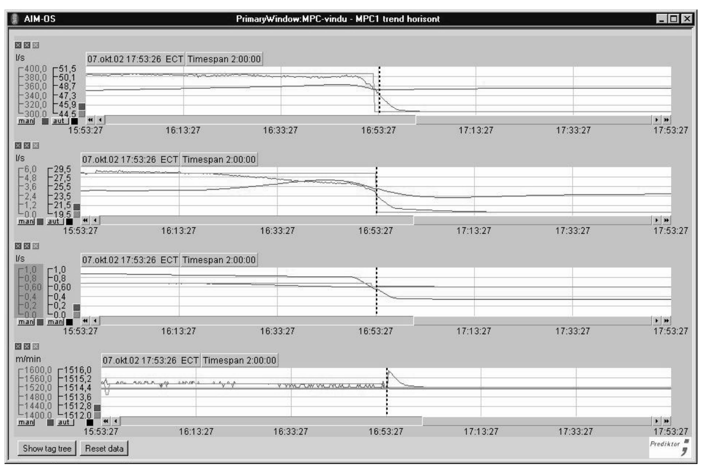

Figure 4.10: In the middle of a grade change at October 7th, 2002.

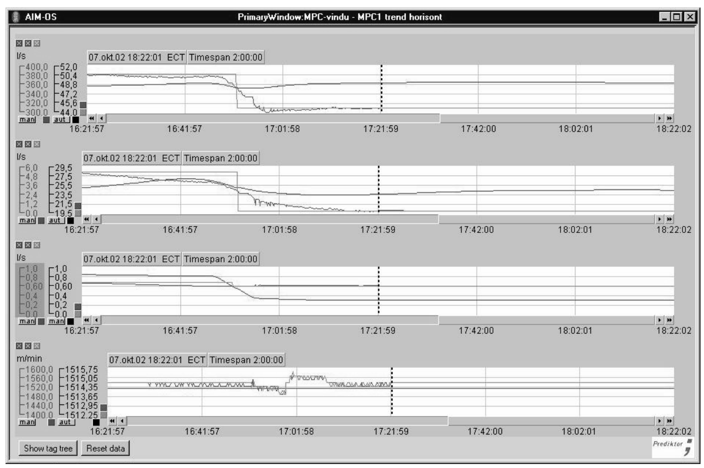

Figure 4.11: Grade change at October 7th, 2002, is finished.

Chapter 5

Roll-out of model based control

5.1 Introduction

Many large- and medium sized industry companies have a number of more or less similar process-units for processing of raw materials or production of finished products. An industrial company which has invested, or is about to invest, in advanced model based control in one of their units / factories, would benefit economically if the model and controller could be efficiently rolled-out at similar units.

The mechanistic model of PM6 at Norske Skog Saugbrugs, Norway, has been developed , and used in a model predictive control (MPC) implementation, and it is of interest to investigate if the model can be applied to other paper machines. At the beginning of Chapter 3, it was argued that the development of a reliable model was the key factor for success in advanced control. Thus, the reuse of the PM6 model to other paper machines is the main focus of this chapter. Specifically, it is investigated if and how the model can be reused at PM4, Norske Skog Saugbrugs, and PM3, Norske Skog Skogn, Norway.

There exists very little published material focusing on how to efficiently roll-out models and controllers in the industry. However, the idea of efficient roll-out of models is not entirely new, e.g. (Glemmestad et al. 2002) emphasize the advantage of reusing the models developed at Borealis, and many commercial simulators include model libraries of process units intended for reuse.

5.2 Roll-out at PM4, Norske Skog Saugbrugs

Process description PM4 at Norske Skog Saugbrugs in Halden, Norway, produce super calendered magazine paper. PM4 started up in 1963 and was rebuild during a period between 1987 to 1993. The production capacity is $125,000$ ton per year, with paper width of 4.65 meters and with a typical velocity of $1,250$ meters per minute

(Sandersen 1999). Both PM6 and PM4 at Norske Skog Saugbrugs produce super calendered magazine paper, but PM6 is 30 years younger, and has more than twice the production capacity of PM4.

The largest differences between PM4 and PM6 are probably found in the thick stock area. At PM4, no filler is added to the thick stock. Thus the only filler present in the thick stock area comes with the flow of broke and recovered stock. At PM6 disc filters are used to reclaim usable fiber and filler particles from the white water tank overflow, while another technology is used at PM4. Starch is a polymer of glucose derived from e.g. corn and potatoes (Scott 1996). Starch is added to the thick stock of PM4 through the TMP flow, while no starch is added at PM6. Starch is mainly added to improve the dry-strength of the paper, however it may also improve fines retention and drainage on the wire, and it may have a negative effect on paper formation[1] (Marton 1996). At PM6 the thick stock pump is manipulated to control the flow of thick stock, while at PM4 the thick stock pump is set at a constant speed and a thick stock valve is manipulated. This difference should be of no concern since the measured flow of thick stock is the flow entering the white water tank in both cases, and the MPC calculates the setpoint for this flow. Whether the lower level controller manipulates a pump or valve to obtain the setpoint, is irrelevant for the MPC.

The accept from the second and third stages of the hydrocyclone arrangement goes to the inlet of the white water tank via the deculator (left chamber) at PM6. At PM4 the accept goes straight to the inlet of the white water tank. This is probably not an important difference since the volume of the left chamber of the deculator is very small. Finally, a difference in the number of stages in the hydrocyclone arrangement can be found; at PM6 a five stage arrangement is used, while it is a seven stage arrangement at PM4.

Model fitting results Open loop experiments were carried out during a 5-hour period on the 10th of December 2002. These experiments were used to find approximate values for gains and time constants in the process, and for model fitting, as described in subsection 3.2.2 and Figure 3.2. Another data set was collected on the 12th of December 2002 for validation of the model. The validation data set was collected partly in open loop and with the process operators manually carrying out some step changes and a grade change. The measured and simulated outputs during validation are shown in Figure 5.1. Note that no state updating takes place during the validation, and only the initial values are given. Some statistics from the validation are given in Table 5.1. The term RMSE in Table 5.1 denotes the Root Mean Square Error value defined by

$$\mathrm{RMSE}_i = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(y_i(t) - \hat{y}_i(t)\right)^2}, \tag{5.1}$$

where N is the number of observations, $y_i(t)$ is the measured value of output i at time t, and $\hat{y}_i(t)$ is the predicted or simulated value of output i at time t.

[1] The distribution of fibres in the paper sheet.

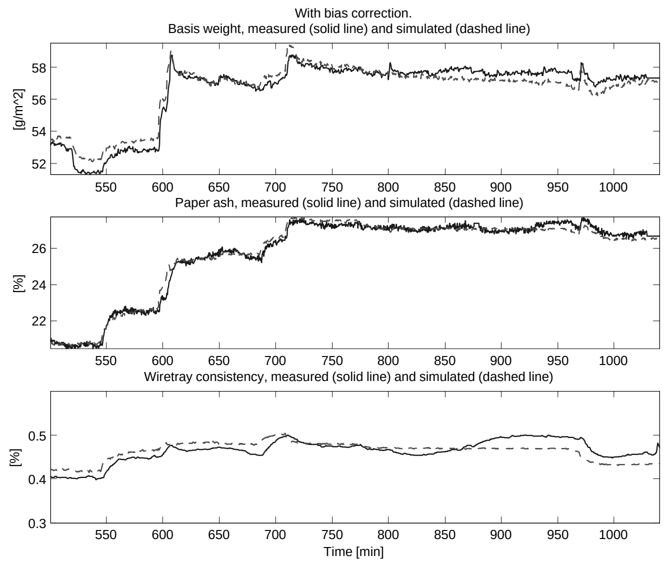

Figure 5.1: Validation of fitted model. The outputs were collected at PM4 on the 12th of December 2002. The validation is carried out by simulating the system with only the initial state values given.

Table 5.1: Statistics from validation of model with PM4 data.

Properties	**Basis weight**	**Paper ash**	**W.t. conc.**
Bias	-0.52	0.97	0.04
RMSE*	0.37	0.19	0.013

*Bias corrected

5.3 Roll-out at PM3, Norske Skog Skogn

Process description Norske Skog Skogn is the largest producer of newsprint in Norway. The production of newsprint started in 1966, and the mill has three paper machines as of today. PM3 is the largest and most modern paper machine at the Skogn mill. The production capacity of PM3 is 227,000 ton per year, with paper width of 8.47 meters, and with a typical velocity of 1,350 meters per minute. The basis weight has a more limited range than the Saugbrugs machines; typical values are 42.5, 45, and 48.8 $\mathrm{g/m^2}$. PM3 started up in 1981 and had a major rebuild/updating in 1995. PM3 is the only paper machine in Norway using DIP[2] for production of newsprint. The DIP content, or the amount of recycled fiber, is approximately 50-55% (Norske Skog 2002), (Heggli 2002). Note that PM3 in Skogn produce newsprint while both PM6 and PM4 at Saugbrugs produce super calendered magazine paper. In terms of production capacity and paper width, PM3 at Skogn, and PM6 at Saugbrugs are comparable.

Filler is added via the DIP and broke flows, thus no other filler is added to the thick stock or short circulation. The thick stock flow is manipulated through the thick stock valve, with the thick stock pump set to a constant speed. The number of stages in the hydrocyclones are 6. The accept from the second stage of the hydrocyclones goes to the inlet of the white water tank, and the accept from the third stage goes to the white water tank. At PM6, the accept from the second and third stage goes to the left chamber of the deculator. The screens and the deculator appear in reverse order at PM3, compared to PM6 and PM4 at Saugbrugs. Also, the retention aid is added before the screens, and not after as is done at PM6.

Model fitting results Figure 5.2 shows the first attempt to fit the PM6 Saugbrugs model to data collected at PM3 Skogn during December, 4th, 2002. The basis weight is the only output excited to any extent in this data set, the paper ash and wire tray concentration being more or less at rest. This is a general feature of PM3 due to the low filler content in the stock. Thus, the multivariable PM6 model does not come to full appraisal at PM3 yet, however there is an increasing trend of using more filler in newsprint, and test runs at PM3 with filler added to the short circulation will soon take place (Heggli 2002).

Studying data from PM3, it is clear that there is not much to gain in terms of stabilizing the process during normal operation. However, during start ups, sheet breaks, and grade changes, efficiency may be improved. Figure 5.3 shows the validation of the model during a grade change. At the beginning of the grade change a sheet break occur. This is recognized in Figure 5.3 by the basis weight and paper ash outputs being frozen at the values that they had immediately prior to the break. When the paper is back on the reel, the measured basis weight is $52\,\mathrm{g/m^2}$, while the setpoint is $48.8\,\mathrm{g/m^2}$. The simulated basis weight is close to the measured basis weight when the paper is back on the reel, and the simulated basis weight follows the measured basis weight closely during the whole simulation. The bias in the basis weight is approximately $0.25\,\mathrm{g/m^2}$. If the controller had relied on the simulated model output during

[2] DIP = De-Inked Pulp, i.e. pulp produced from recovered paper.

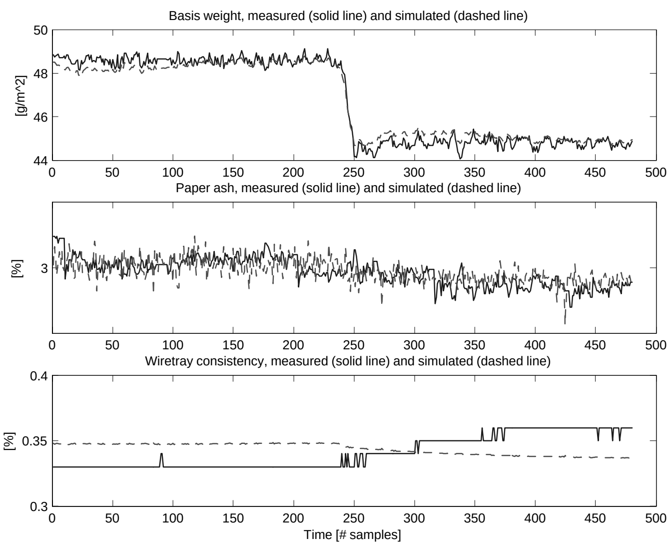

Figure 5.2: First trial fitting of PM6 Saugbrugs model to data from PM3 Skogn. Data collected at 4th of December, 2002, with 30 seconds sampling time (resampled from 5 seconds sampling time).

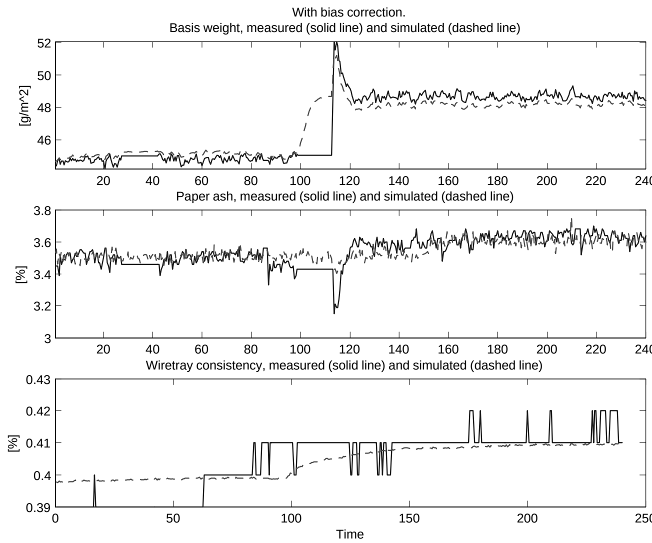

Figure 5.3: Validation of fitted model. The outputs were collected at Norske Skog Skogn PM3 on the 12th of December 2002 during a grade change. The validation is carried out by simulating the system with only the initial state values given.

the combined grade change and sheet break, the basis weight would probably have been close to the setpoint when the paper was back on the reel. Thus, less off-spec paper would be produced.

Figure 5.4 shows the basis weight and wire tray concentration outputs during a start up. The basis weight measurement is frozen at $44.8\,\mathrm{g/m^2}$ during the first 330 minutes. In Figure 5.5, it is shown in detail what happens to the basis weight measurement and simulated output when the paper is back on the reel for the first time after the start up. The measured basis weight is close to $49\,\mathrm{g/m^2}$, with the setpoint being $45\,\mathrm{g/m^2}$. This deviation was more or less predicted by the model simulation, thus the basis weight could have been much closer to the setpoint after the start up if the controller had relied on the simulated model outputs when the measurements were not available.

5.4 Comments on roll-out of PM6 model

Data and information from PM4 at Norske Skog Saugbrugs, and PM3 at Norske Skog Skogn were gathered in order to investigate the possibility to roll-out the PM6 model at other paper machines. Fitting and validation of the model are very promising. No changes to the model were carried out, except for tuning of parameter values, and still the validation results are good. The time spent on fitting and validating the

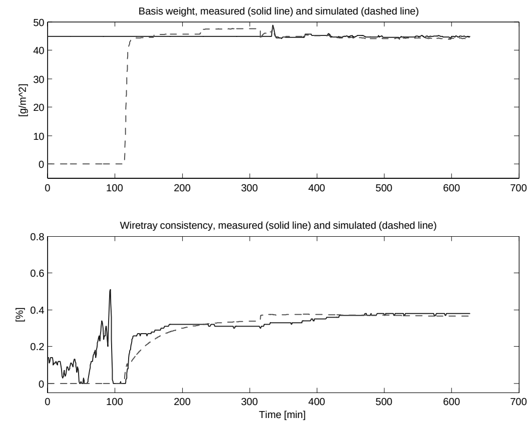

Figure 5.4: Validation of fitted model. The outputs were collected at Norske Skog Skogn PM3 on the 11th and 12th of December 2002 during a start up. The validation is carried out by simulating the system with only the initial state values given. During the first 330 minutes paper is not produced and the basis weight measurement is frozen at $44.8\,\mathrm{g/\,m^2}$.

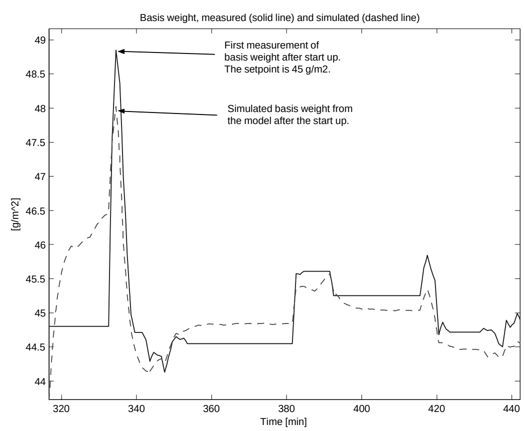

Figure 5.5: Validation of basis weight during start up. The outputs were collected at Norske Skog Skogn PM3 on the 11th and 12th of December 2002. The validation is carried out by simulating the system with only the initial state values given. During the first 330 minutes paper is not produced and the basis weight measurement is frozen at $44.8\,\mathrm{g/\,m^2}$.

PM6 model to PM4 and PM3 are approximately 1% of the time spent on developing the original model. This should be a strong incentive for focusing on mechanistic modeling in industries were there are many similar production lines or units.

Chapter 6

List of papers in thesis

A. Hauge, T.A. and Lie, B. (2000). *Simulation for Advanced Control of a Paper Machine: Model Complexity and Model Reduction*, in proceedings of the 41st SIMS simulation Conference, September 18-19, 2000, Technical University of Denmark, Kgs. Lyngby, Denmark, p 135-154.

   A few corrections are made to the original paper.

B. Hauge, T.A., Ergon, R., Forsland, G.O., Slora, R. and Lie, B. (2000). *Modeling, Simulation and Control of Paper Machine Quality Variables at Norske Skog Saugbrugs, Norway*, in proceedings of the PIRA conference "Scientific & Technological Advances in the Measurement & Control of Papermaking", December 11-12, 2000, Edinburgh, UK.

   A few corrections are made to the original paper.

C. Hauge, T.A. and Lie, B. (2001). *Paper Machine Modeling at Norske Skog Saugbrugs: A Mechanistic Approach*, in proceedings of the 42nd SIMS Simulation Conference, October 8-9, 2001, Telemark University College, Porsgrunn, Norway, p 119-154.

   Also in *Modeling, Identification and Control*, 23(1), p 27-52. (An updated and condensed version of the SIMS 2001 paper).

   The version given here is the SIMS paper with updates from the MIC paper, but not condensed.

D. Hauge, T.A., Slora, R. and Lie, B. (2002). *Model Predictive Control of a Norske Skog Saugbrugs Paper Machine: Preliminary Study*, in proceedings of Control Systems 2002, June 3-5, Stockholm, Sweden, p 75-79.

   Extended version.

E. Lie, B., Dueñas Díez, M., and Hauge, T. A. (2002). *A Comparison of Implementation Strategies for MPC*, in Proceedings of International Symposium on Advanced Control of Industrial Processes, June 10-11, 2002, Kumamoto, Japan.

   A few corrections are made to the original paper.

F. Hauge, T.A., Slora, R., and Lie, B. (2002). *Application of a Nonlinear Mechanistic Model and an Infinite Horizon Predictive Controller on Paper Machine 6 at Norske Skog Saugbrugs*, Submitted to Journal of Process Control.

   Extended version.

G. Hauge, T.A., Slora, R., and Lie, B. (2002). *Roll-out of model based control with application to paper machines*, Submitted to Journal of Process Control.

   Extended version.

Chapter 7

List of other contributions

1. Hauge, T.A. (2002). Modeling and control of PM6 at Norske Skog Saugbrugs, Invited lecture at MSc. course “Modeling of dynamic systems” at Telemark University College, Norway, November 18, 2002 (in Norwegian).

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