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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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Contents

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. In this paper we study if the model can be applied to other paper machines (roll-out), and we discuss advantages and disadvantages of different modeling approaches. The paper machines studied are PM4 at Norske Skog

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Saugbrugs, and PM3 at Norske Skog Skogn, Norway. PM6 is a new and modern paper machine producing SC (Super Calendered) magazine paper. PM4 also produces SC paper but the machine is older and smaller than PM6. PM3 produces newsprint and has a size comparable with PM6. Fitting and validation of the model to PM4 and PM3 are very promising. No structural changes to the model 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.

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 main idea of this paper is to investigate how a model and controller developed for a specific industrial process can be applied to similar processes. A mechanistic model of paper machine 6 (PM6) at Norske Skog Saugbrugs, Norway, has been developed in (Hauge & Lie 2002), and used in a model predictive control (MPC) implementation (Hauge, Slora & Lie 2002). In this paper we investigate if and how the model can be reused at PM4, Norske Skog Saugbrugs, and PM3, Norske Skog Skogn, Norway.

The papermaking process is the only process studied in this paper, 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 for PM6 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)).

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.

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, 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.

This paper is organized as follows. In Section 2, various approaches to modeling, with advantages and disadvantages, are discussed. Section 3 summarizes the work on modeling and model predictive control (MPC) carried out at paper machine 6 (PM6), Norske Skog Saugbrugs. Roll-out of the model on PM4, Norske Skog Saugbrugs, is described in Section 4, and similarly for PM3, Norske Skog Skogn, in Section 5. Finally, some conclusions are given in Section 6.

2 Modeling approaches

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. In the literature one often encounter terms like black box modeling, system identification, time series analysis, and behavioral modeling. All these terms basically mean the same as empiric modeling. 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). 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 paper we include grey box models whenever we speak of mechanistic models.

Table 1 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, Lohmann & Marquardt 1998) it is indicated that the development cost for an empiric model is about 1/10 compared to a mechanistic model. Another positive feature of empiric models is that they often have a simple structure (linear and time invariant) which

Table 1: 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.

leads to quick and easy simulation, analysis, and design of control algorithms. If one has access to experimental data, 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 are 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 the 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. That is 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, Fu, Nuyan, Kuusisto & Huhtelin 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 hard to model their effect on the model outputs empirically. 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.

3 Modeling and MPC at PM6, Norske Skog Saugbrugs

Norske Skog Saugbrugs in Halden, Norway, is one of the largest manufacturers of uncoated super calendered magazine paper in the world. The total production capacity of the mill is $550,000$ ton per year. The largest paper machine (PM) at the Saugbrugs mill is PM6, accounting for more than half the total production capacity. PM6 was build in the early 1990's and produce paper with width of 8.62 meters, and with a typical velocity of 1550 meters per minute.

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 content of filler. For newsprint the amount of filler is typically between 0-10%. Due to the high filler content in magazine paper, the couplings between important input and output variables are rather dominant.

3.1 Process description

A simplified drawing of PM6 is shown in Figure 1. 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 fed to the machine chest with a controlled total consistency[1]. Between the mixing and machine chests, filler is added at a

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

constant rate. The fillers used in paper production depends on the end-user requirements, however some of the typical fillers are kaolin, chalk, talc, and titanium dioxide (Bown 1996). About two thirds of the filler particles used at PM6 is added to the thick stock, the rest 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 to 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[2] 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 is two parallel screens, which separates 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 process is a key 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 fine mesh, 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 draining. 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 accumulated on the reel before it is moved on to further processing.

3.2 The process model

The process model is described in detail in e.g. (Hauge & Lie 2002) and only a brief description will be given here. Note that some modifications have been carried out to the model detailed in (Hauge & Lie 2002), as compared to the model implemented at PM6. The most prominent modification is that a first order empiric model that was

[2] White water is the drainage from the wire. It is stored in the white water tank.

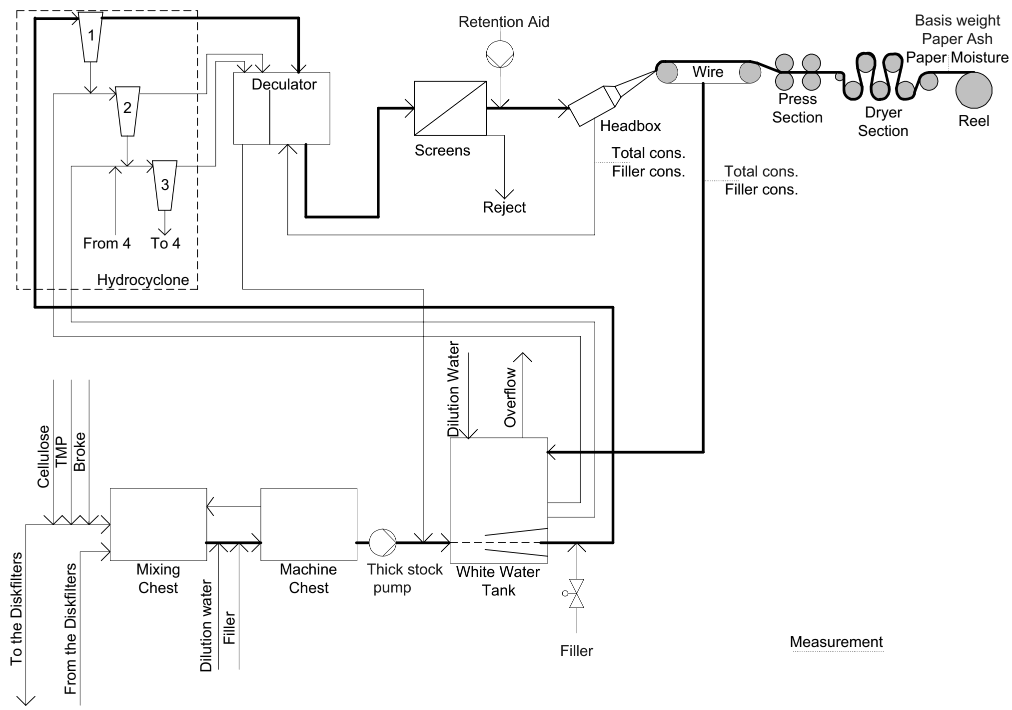

Figure 1: Simplified drawing of PM6, Norske Skog Saugbrugs.

added to capture neglected and unknown dynamics in the process, has been removed.

The 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 "final" model consists of a third order nonlinear mechanistic model based on physical and chemical laws. The structure of the developed process model is

$$\begin{aligned} \dot{\bar{x}} &= \bar{f}(\bar{x}, \bar{u}, \bar{d}, \bar{\theta}) \\ \bar{y} &= \bar{g}(\bar{x}, \bar{u}, \bar{d}, \bar{\theta}), \end{aligned} \tag{1}$$

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 indicate 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 manipulated inputs $\bar{u}$, the outputs $\bar{y}$, the states $\bar{x}$, and the measured disturbances $\bar{d}$ are

$$\begin{aligned} \bar{u}^T &= [\bar{u}_{TS}, \quad \bar{u}_F, \quad \bar{u}_{RA}] \\ \bar{y}^T &= [\bar{y}_{BW}, \quad \bar{y}_{PA}, \quad \bar{y}_{WC}] \\ \bar{x}^T &= \left[\bar{C}_{R,fil}, \quad \bar{C}_{WT,fil}, \quad \bar{C}_{D,fib}\right] \\ \bar{d}^T &= \left[\bar{C}_{\mathrm{TS,tot}}, \quad \bar{C}_{\mathrm{TS,fil}}, \quad \bar{v}, \quad \bar{f}\right], \end{aligned} \tag{2}$$

where the inputs 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 are the basis weigh (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 variability of other short circulation variables. $\bar{C}_{R,fil}$ 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 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.

3.3 Model fitting from experimental data

The developed model 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. The model used 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 $17\,\mathrm{m}^3$ (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, i.e. we estimate 19 parameters including two biases and three initial ODE values.

The function `lsqnonlin` in the Matlab Optimization toolbox is used for solving the minimization problem

$$\hat{\theta} = \arg\min_{\theta} J(\theta), \tag{3}$$

subject to the constraints

$$\theta_{\min} \leq \hat{\theta} \leq \theta_{\max}, \tag{4}$$

where θ is the parameter vector and $\hat{\theta}$ is the estimated parameter vector. Thus, we wish to find the parameter values (arguments) $\hat{\theta}$ that minimize the criterion $J(\theta)$. The criterion used is

$$J(\theta) = e^T(\theta) \cdot Q \cdot e(\theta), \tag{5}$$

where e is a vector of errors, and Q is a diagonal weighting matrix. The function relies on the Levenberg-Marquardt algorithm in its search for the optimal parameter values (The MathWorks, Inc. 2000). The errors e are calculated by simulating the system, with only the initial conditions given. The error is then

$$\varepsilon(t) = \hat{y}(t|0) - y(t), \tag{6}$$

where $y(t)$ is the measured output at time t, and $\hat{y}(t|0)$ is the model output at time t given only the initial conditions. The error vector for output i is then

$$e_i^T(\theta) = \begin{bmatrix} \varepsilon_i(1) & \varepsilon_i(2) & \cdots & \varepsilon_i(t) & \cdots & \varepsilon_i(N-1) & \varepsilon_i(N) \end{bmatrix}. \tag{7}$$

where N is the number of samples in the data set.

Traditional system identification (see e.g. (Ljung 1999)) is in most cases carried out using a one-step-ahead predictor (corresponding to $\varepsilon(t) = \hat{y}(t|t-1) - y(t)$), 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 is used for model predictive control (MPC). Then, it seems natural to use the simulation approach in the parameter estimation algorithm. The simulation approach results in a deterministic model, and it is also necessary to identify or model the noise.

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 achieved by introducing

$$\theta = S \times \tilde{\theta}, \tag{8}$$

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 6. 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 to 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.

3.4 Validation and re-tuning of 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 another data set (failing to simulate outputs close to measured outputs). Many methods for validation exist, however in our opinion any proper validation method should at least 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 in our opinion a proper validation method, as one will e.g. not discover whether slow varying disturbances, drifts and trends, eventually will ruin the properties of the model. 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.

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 and found to work well, for model fitting, validation and re-tuning of the model. The procedure is also pictorially presented in Figure 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 whether 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.

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.

3.5 Model Predictive Controller (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 other systems, the setpoint is constant into the future, so once a change in the setpoint is made, the controller will respond immediately, giving the operators no time to consider how wise the response is;
- develop an interface that will gain 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

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

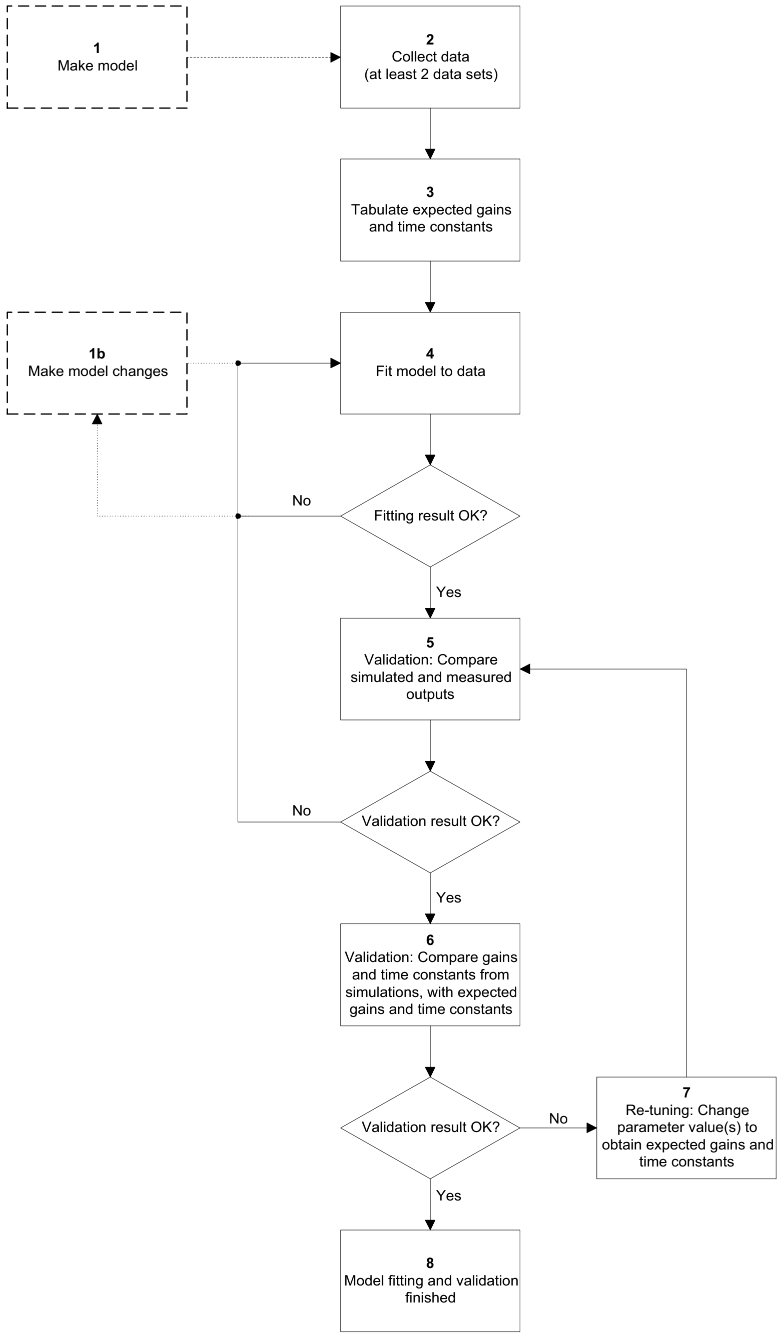

Figure 2: Procedure for model fitting and validation.

The use of MPC, a nonlinear model, an 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.

3.6 Results

The main objective of the project “Stabilization of the wet end at PM6” was to increase the total efficiency by 0.47%. This objective can hardly be validated, 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 set-points 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.

4 Roll-out at PM4, Norske Skog Saugbrugs

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).

4.1 Process description

A simplified drawing of PM4 at Norske Skog Saugbrugs is shown in Figure 3. Only differences between PM4 and PM6, described in subsection 3.1, will be commented on. Note that 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[3] (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.

4.2 Model fitting results

Figure 4 shows the first attempt to fit the PM6 model to a noisy and oscillating operational data set collected from PM4 during October 18-19, 2002. Based on this first attempt to fit the model, it was decided to carry out experiments to obtain more informative data.

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 Section 3.4 and Figure 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 inputs are shown in Figure 5, and the measured and simulated outputs are shown in Figure 6. 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 2. The term RMSE in Table 2 denotes the Root Mean Square Error value defined by

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

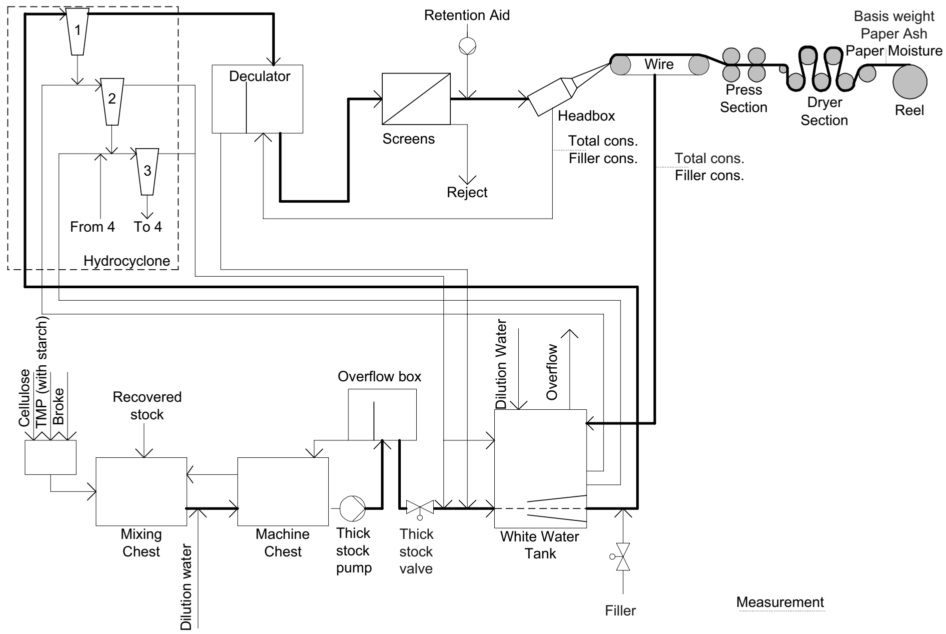

Figure 3: Simplified drawing of PM4, Norske Skog Saugbrugs.

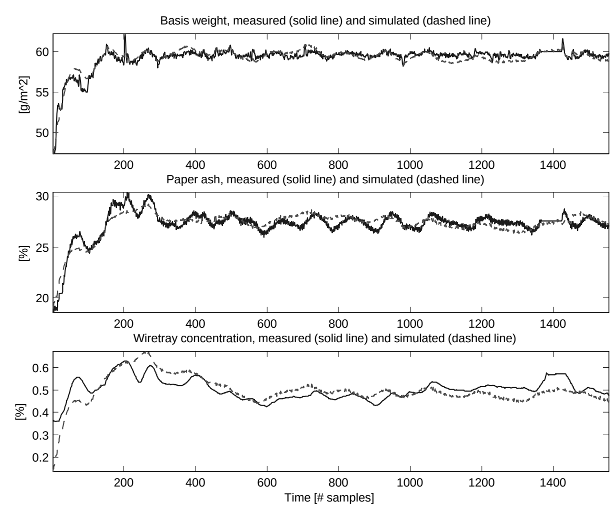

Figure 4: First trial fitting of PM6 model to data from PM4.

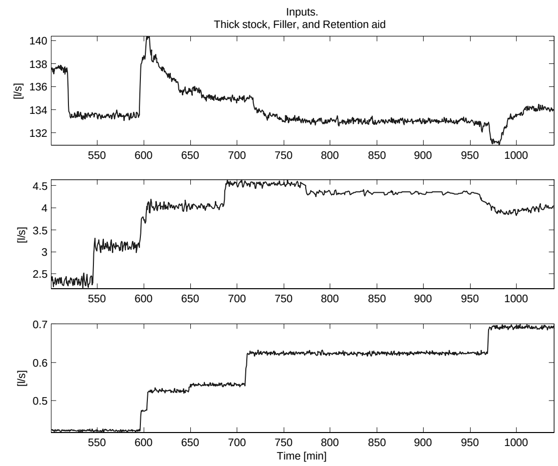

Figure 5: Inputs at PM4 on the 12th of December 2002. The data set were used for validation of the fitted model.

Table 2: 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

$$\mathrm{RMSE}_i = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(y_i(t) - \hat{y}_i(t)\right)^2}, \tag{9}$$

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.

5 Roll-out at PM3, Norske Skog Skogn

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

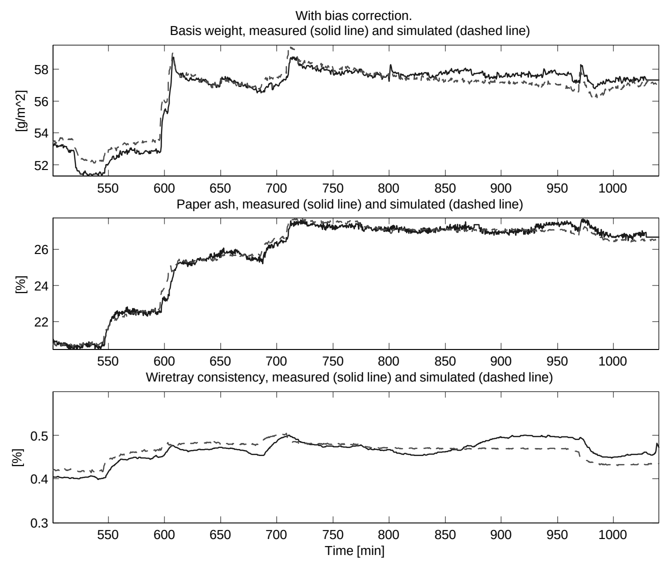

Figure 6: Validation of fitted model. The outputs were collected at PM4 on the 12th of December 2002. The validation is carried out by simulating the system with only the initial state values given.

machine in Norway using DIP[4] for production of newsprint. The DIP content, or the amount of recycled fiber, is approximately 50-55% (Norske Skog 2002), (Heggli 2002).

5.1 Process description

A simplified drawing of PM3 at Norske Skog Skogn is shown in Figure 7. Only differences between PM3 at Skogn and PM6 and PM4 at Saugbrugs, described in subsection 3.1, will be commented on. 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.

5.2 Model fitting results

Figure 8 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 9 shows the inputs during a grade change. Note that the filler input is zero throughout the data set because no filler is added to the short circulation. At the beginning of the grade change a sheet break occur. This is recognized in Figure 10 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 the combined grade change and sheet break, the basis weight would

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

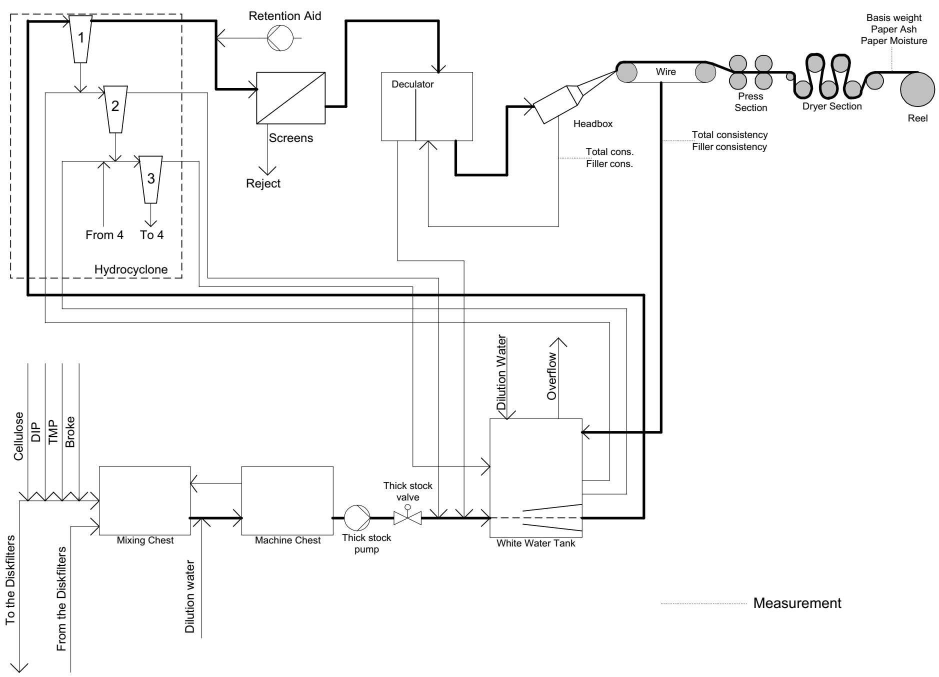

Figure 7: Simplified drawing of PM3, Norske Skog Skogn.

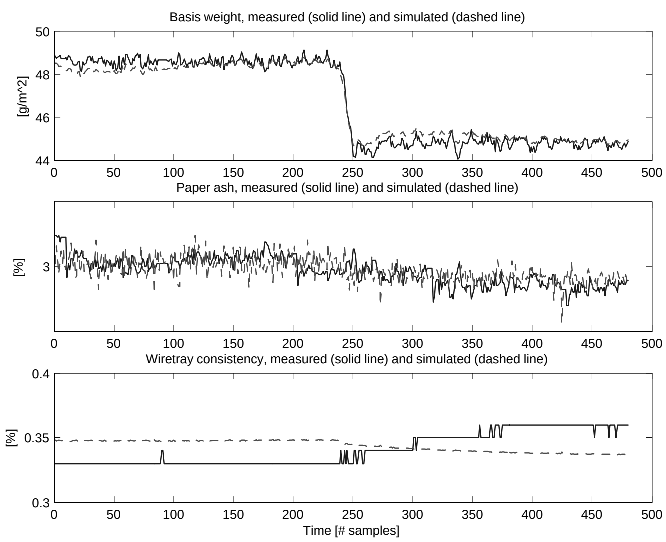

Figure 8: First trial fitting of PM6 Saugbrugs model to data from PM3 Skogn. Data collected at 4th of December, 2002, with 30 seconds sampling time (resampled from 5 seconds sampling time).

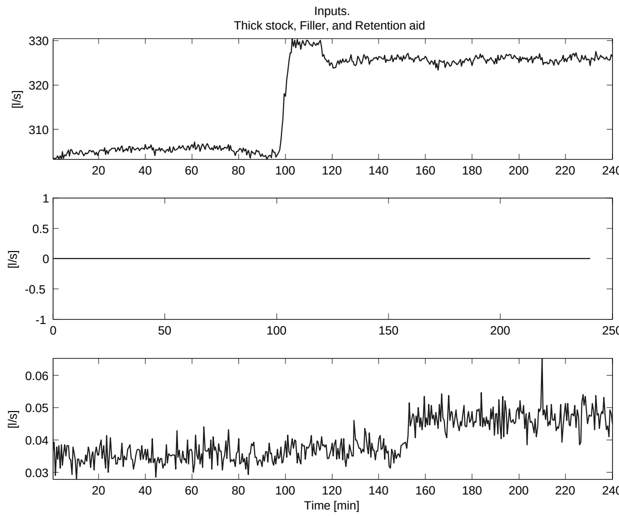

Figure 9: Inputs at Norske Skog Skogn PM3 on the 12th of December 2002 during a grade change. The data set were used for validation of the fitted model.

probably have been close to the setpoint when the paper was back on the reel. Thus, less off-spec paper would be produced.

Figure 11 shows the inputs during a start up, and Figure 12 shows the basis weight and wire tray concentration outputs. The basis weight measurement is frozen at $44.8\,\mathrm{g/\,m^2}$ during the first 330 minutes. In Figure 13, 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.

6 Conclusions

A mechanistic nonlinear model of the wet end of PM6 at Norske Skog Saugbrugs has been developed, and used in an MPC application. Variability in important quality variables and consistencies in the wet end have been reduced substantially, compared to the variability 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.

Data and information from PM4 at Norske Skog Saugbrugs, and PM3 at Norske

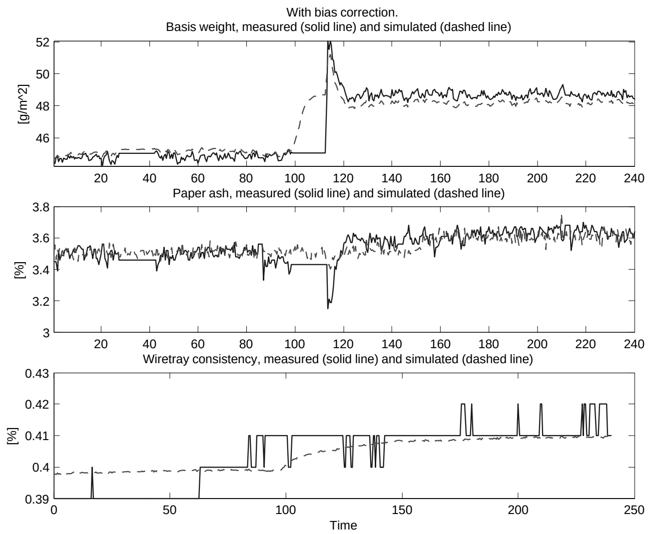

Figure 10: Validation of fitted model. The outputs were collected at Norske Skog Skogn PM3 on the 12th of December 2002 during a grade change. The validation is carried out by simulating the system with only the initial state values given.

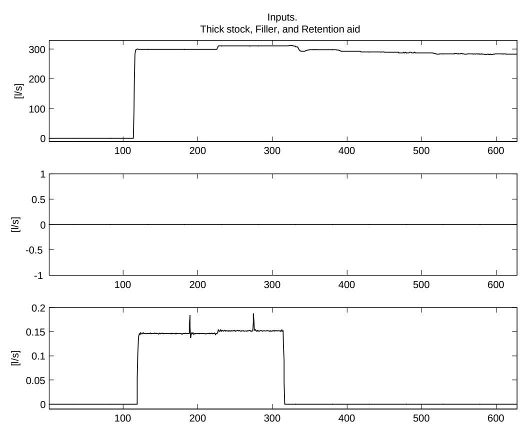

Figure 11: Inputs at Norske Skog Skogn PM3 on the 11th and 12th of December 2002 during a start up. The data set were used for validation of the fitted model.

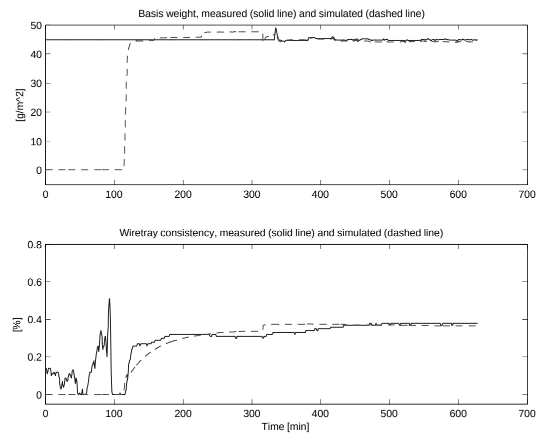

Figure 12: Validation of fitted model. The outputs were collected at Norske Skog Skogn PM3 on the 11th and 12th of December 2002 during a start up. The validation is carried out by simulating the system with only the initial state values given. During the first 330 minutes paper is not produced and the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

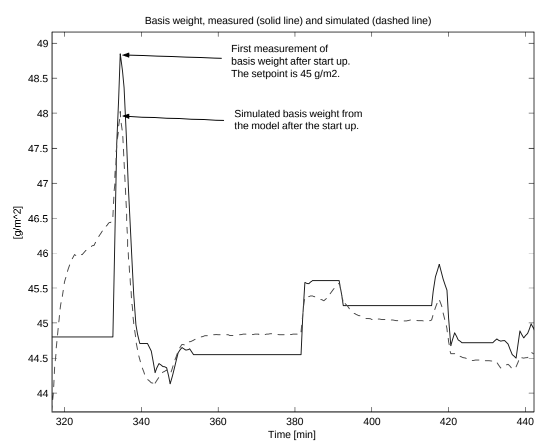

Figure 13: Validation of basis weight during start up. The outputs were collected at Norske Skog Skogn PM3 on the 11th and 12th of December 2002. The validation is carried out by simulating the system with only the initial state values given. During the first 330 minutes paper is not produced and the basis weight measurement is frozen at $44.8\,\mathrm{g/\,m^2}$.

Skog Skogn were gathered in order to investigate the possibility to roll-out the model and controller on other paper machines. Fitting and validation of the model were very promising. No changes to the model were carried out, except for tuning of parameter values, 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.

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