Paper B

Modeling, Simulation and Control of Paper Machine Quality Variables at Norske Skog Saugbrugs, Norway

A few corrections are made to the original paper.

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Modeling, Simulation and Control of Paper Machine Quality Variables at Norske Skog Saugbrugs, Norway

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Abstract

In this paper we focus on an ongoing project at Norske Skog Saugbrugs, Norway, for stabilization of the wet end of paper machine 6 (PM6). A high-order order mechanistic model is developed, and model reduction is studied by simulation. Closed loop experiments on PM6 is described and carried out, and empiric models are identified and validated. The models will be used in a model predictive control (MPC) structure. A solution for estimating missing measurements during sheet breaks is presented and demonstrated with simulations.

Keywords: Paper machine, dynamic model, optimal estimation, system identification, closed loop identification, model reduction, model predictive control

1   Introduction

At Norske Skog Saugbrugs, Norway, a project has been initiated to stabilize the wet end of paper machine 6 (PM6). Norske Skog Saugbrugs is the world's second largest manufacturer of uncoated magazine paper (SC) (Norske Skog 2000), and the mill incorporates three paper machines, of which PM6 is the largest and most modern one (build in the 1990's). The project "Stabilization of the wet end of PM6" will be described in some detail here, focusing on the results so far and also briefly discussing future actions.

The objects of the project are to reduce the number of sheet breaks, reduce the down time when sheet breaks occur and to substantially reduce the variability in key variables such as basis weight, paper ash, white water consistencies, etc. Another important objective is to investigate how the methods developed in this project can be efficiently applied on other paper machines within Norske Skog.

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The basic idea is to model selected parts of the paper machine and use model predictive control (MPC) for improving the stability of selected variables. A similar approach is reported in (Lang, Tian, Kuusisto & Rantala 1998), although there are several important differences, notably the use of a mechanistic model in this project. The selected variables are the basis weight, the paper ash content and the white water total consistency.

There are basically two different approaches to modeling for control: i) Mechanistic modeling, in which physics, material balances, etc. form the basis of the model, and ii) Empirical modeling, in which collected input-output data are used to fit a non-physical model structure to the data. Both mechanistic and empiric models are presented in this paper and the two approaches have some distinct features which will be discussed later. The mechanistic model of PM6, with the three selected output variables and three selected input variables, is implemented in MATLAB. This work is thoroughly described in (Hauge & Lie 2000b). The model, which is a non-linear state-space model, is quite large and complex, and perhaps not a good candidate for model based control. Input-output data are collected from the process and these indicate that a transfer matrix with elements consisting of first- or second-order models with time delays may be sufficient to describe the process behavior at a given operating condition (Slora 1999). Thus, we wish to reduce the complexity of the mechanistic model so that it is more suitable for advanced control purposes. In this paper we approach the simplification problem by i) system identification methods - i.e. we identify empirical "low-order" models by various well established methods, and ii) physical knowledge - i.e. we utilize our physical knowledge about the process to reduce the model. This leads to a set of models of various size and complexity, and these are compared by their prediction abilities at different operating conditions.

Included in this paper are also results from identification and validation of dynamic models from real time data. The experiments were carried out in September-October, 2000, and in this paper we chose to focus on empirical models, saving the mechanistic model fitting for future work. Experiment design problems are addressed and discussed to some extent. Closed loop data are used with various identification methods, giving low-order linear models.

During sheet breaks the basis weight and paper ash measurements are lost, leading to serious problems for the controller. An alternative to "freezing" the controlled inputs is to estimate the missing measurements and let the controller use the estimates during sheet breaks. An estimator could be mechanistic or empiric, and in this paper we focus on a theoretically optimal empiric estimator. The estimator utilizes system inputs and also secondary measurements (measurements which are of less importance) as estimator inputs. The optimal estimator is based on an underlying Kalman filter and an output error (OE) model structure (Ergon 1999b).

The paper is organized as follows: In Section 2 an overview of PM6 is presented. Section 3 elaborates on mechanistic and empiric modeling of PM6 using simulated data, while real-time data are used in Section 4. Section 5 deals with an optimal solution for estimation of missing measurements during sheet breaks. In Section 6 a possible future model predictive control structure of PM6 is presented in addition

to several ongoing projects for disturbance rejection in connection with the models. Finally, Section 7 summarizes this paper and presents some conclusions.

2   The Process

A simplified description of the paper machine is given in Figure 1. A short description of some important aspects is given next, while a more thorough description is found in (Hauge & Lie 2000a) and (Hauge & Lie 2000b).

Filler is added both to the thick stock and to the short circulation. Various types of fillers are added depending on the required properties for the finished paper. The behavior of the various kinds of fillers is very distinct, at least regarding the retention aid. However, these differences will not be seen in the present paper, as only one kind of filler is added to the stock during experimentation and simulation.

The first cleaning process is a five stage hydrocyclone arrangement, mainly intended to separate heavy particles 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 separates larger particles from the stock. Retention aid is added to the stock at the outlet of the machine 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 mechanism is the key for retaining small fiber fragments (fines) and filler particles on the wire. Non-flocculated fines and filler particles will in general be too small to be retained on the wire, although mechanical entrapment can be a significant mechanism (Bown 1996), (Orccotoma, Paris & Perrier 1999).

3   Modelling and identification from simulated data

3.1   A mechanistic approach

A black-box overview of the system is given in Figure 2. The manipulated inputs to the system are the amount of thick stock (u_t), the amount of filler added to the short circulation (u_f), and the amount of retention aid (u_r). The outputs from the system are the basis weight (y_w), the paper ash content (y_a), and the white water total consistency (y_c). The basis weight and the paper ash content are measured between the dryer section and the reel, while the white water total consistency is measured in the flow from the wire to the white water tank.

The model is basically covering the elements (chests, tanks, pipes, etc.) found in Figure 1. Typically, there are mass-balances of (longer) fiber, fiber fines, and various kinds of fillers for every significant volume, i.e.

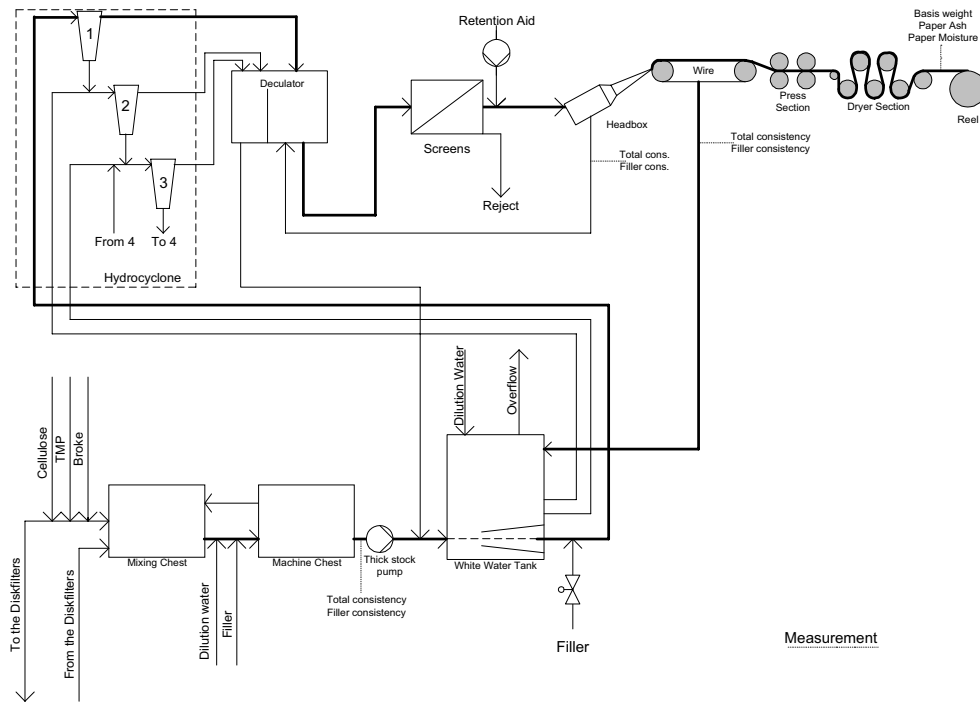$$\frac{dm_i}{dt} = \sum_j w_{i,j}, \tag{1}$$
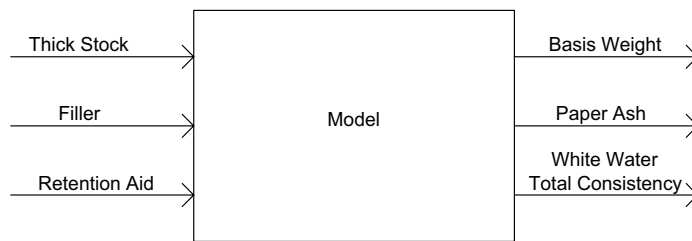
Figure 1: Simplified sketch of the paper machine.

Figure 2: Inputs and outputs from the model.

where m_i is mass of component i in some volume, and $w_{i,j}$ is mass flow j of component i into this volume. In the short circulation there are also mass-balances for floccu- lated components and retention aid. Most pipelines are modeled by partial differential equations (time delays), i.e.

$$\frac{\partial C_i}{\partial t} = -v \cdot \frac{\partial C_i}{\partial x}, \qquad (2)$$

where C_i is the concentration of component i, and v is the velocity of mass flow in the pipeline. The addition of retention aid causes fibers and fillers to flocculate. The flocculation takes place in the short circulation, and is here modeled by second-order kinetic equations like

$$\frac{\partial C_{\text{floc},i}}{\partial t} = -v \cdot \frac{\partial C_{\text{floc},i}}{\partial x} + \frac{k_i}{\rho} \cdot C_i \cdot C_{\text{ret.aid}}, \qquad (3)$$

where $C_{floc,i}$ is the concentration of flocculated mass of component i, C_i is the concen- tration of component i (non-flocculated), k_i is a flocculation constant, ρ is the density of the mass flow, and $C_{ret.aid}$ is the concentration of retention aid. The flocculation term in Equation 3 is obviously too simple for describing the complicated flocculation (and adsorption) process, but it may be sufficient for a model for control. The mech- anistic model is not yet validated with real data, and should the validation fail then there are some alternative, and more complicated, flocculation terms which can be derived from the literature. Several sources, e.g. (Swerin, Ödberg & Wågberg 1996) and (Moudgil, Shah & Soto 1987), state that the flocculation rate can be expressed as

$$F = kEN_0^2, \qquad (4)$$

where k is a rate constant, E is a flocculation efficiency factor often modelled by $E = \theta(1 - \theta)$ where θ is the fractional coverage of the solid surface by polymer, and where finally N_0 is the number of particles. (Shirt 1997) uses the following second- order kinetic equation in his dynamic simulation model

$$\frac{dC_{ij}}{dt} = k^{ij} C_i C_j \theta_i^+ \theta_j^- \left(\frac{V_i V_j}{V_i + V_j} \right), \qquad (5)$$

$$\frac{d\theta}{dt} = k_{\text{att}}(n_0 - \theta)(1 - \theta) - k_{\text{det}}\theta,$$

where C_{ij} is consistency of flocs formed from components i and j, C_i and C_j are consistencies of component i and j, θ_i^+ is the fractional coverage of component i by cationic polymer, θ_j^- is fractional coverage of component j by anionic polymer, V_i and V_j are volumes of individual component particles i and j, k_{att} and k_{det} are attachment and detachment rate constants respectively, and finally n_0 is the dosage of polymer relative to the amount required to completely cover the particle surface. Shirt's model is based on a retention aid system with one anionic polymer and one cationic polymer, and is not directly applicable to the PM6 model where only cationic polymer is used. However, from experiments carried out in this project it is observed that certain important aspects which are covered by Shirt's model (Equation 5) are

hardly explained by the flocculation term in Equation 3. It is, for example, observed that the wire tray consistency is reduced when the thick stock flow is increased. This can not be explained by a flocculation term as in Equation 3, and a certain modification is probably necessary.

Elements like the screens, headbox and wire are basically modeled with static/algebraic equations, considering the relatively small volumes involved.

The number of ordinary differential equations (ODE) is 34, and there are 104 partial differential equations (PDE). The PDE's are discretized in x-direction into five ODE's each, bringing the total number of ODE's to 554. In this paper we omit the model for the thick stock, thus the system to study is between the thick stock pump and the reel. The reason for this being that new methods for controlling and calculating the total consistency and ash consistency in the thick stock are implemented at PM6 (more on this in Section 6), thus making the thick stock model superfluous. The number of ODE's and PDE's are thus down to respectively 28 and 100, making the total number of ODE's (after discretization) 528.

3.2 Reduced order mechanistic models

The full scale model is based on physical and chemical laws and balances. In this section we use our physical knowledge about the process, along with common sense, to reduce the complexity and size of the model. Filtered PRBS's (Pseudo Random Binary Signals) are used as test inputs to the system. This type of input is widely used in identification experiments for linear systems/models (Ljung 1999) (Söderström & Stoica 1989). The data are collected in the neighborhood of a typical operating condition of the paper machine.

An RMSE (root mean square error) criterion

$$RMSE_i = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (y_i(t) - \hat{y}_i(t))^2}, \qquad (6)$$

were used for comparing the identification and validation of the various models. Equation 6 gives the RMSE for output i, N is the number of observations, $y_i(t)$ is the simulated output i from the full scale model at time t and $\hat{y}_i(t)$ is the simulated output i at time t from a reduced order model. The i's in the 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 full scale model responses y_i, before the RMSE's are calculated.

The RMSE is calculated for various reduced models, and we chose to concentrate on a 38th order model, an 87th order model and a 161th order model for the comparison with other models. For the 38th order model we also chose to optimize the behavior by tuning some key parameters in the model. These parameters are the volumes in the deculator and in a reject tank between the fourth and fifth stage of the hydrocyclones, and the filler and fines flocculation constants. The physical foundation of the model is only negligibly degraded by the tuning, although e.g. the optimized volumes no longer have the correct physical value.

The reduction in computational time from the 161th order model to the 38th order model was approximately 50%, while the reduction from the full scale model to the 38th order model was more than 80%.

The simplifications   In a model reduction effort it is natural to look at the discretization of the PDE's. In the full scale model each pipeline is discretized into 5 volumes making the pipeline delays the largest contributor to the number of state variables in the model. Simulation showed that by replacing every PDE outside of the main flow (thick line in Figure 1) by one ODE, the model behavior was essentially the same. This immediately reduced the number of states from 528 to 256. In addition the pipelines between the machine chest and white water tank and between the white water tank and the first stage of the hydrocyclones could also be discretized into one volume without affecting the model behavior too much. These simplifications combined with several lumped volumes in the hydrocyclones, and the inclusion of the volume of the pipeline between the deculator (left side) and the white water tank into the deculator (left side) gave the 161th order reduced model.

The 87th and 38th order models are the results of a continuation of reductions and simplifications on the 161th order model. Thus, in the 38th order model the remaining volumes are the white water tank volume, a lumped hydrocyclone reject tank volume, lumped deculator volumes ("right" and "left" side volume) and the volume of the pipeline between the screens and the headbox. More details on the simplifications can be found in (Hauge & Lie 2000a).

Further model simplifications are hard to attain without degrading the physical foundation of the model to a larger extent. However, by allowing the model to be semi mechanistic it is possible to reduce the number of states considerably. A low-order semi mechanistic model is being developed at the moment.

3.3   Empiric models

In this section, several black-box identification schemes will be used to identify "simple" linear models. Input-output data from the full scale model are collected, and models will be identified by prediction error and subspace methods. The data are collected in the neighborhood of a typical operating condition of the paper machine.

Transfer matrix with first- or second-order elements with time delays   The responses of the process to step inputs are saved on file. In turn, the data from one input and one output are used to fit the parameters in a first- or second-order model (transfer function) with time delay:

$$y(s) = \frac{K}{\tau_1 s + 1} e^{-\tau_2 s} \cdot u(s) \tag{7}$$

$$y(s) = \frac{K}{\tau_1^2 s^2 + 2\zeta \tau_1 s + 1} e^{-\tau_2 s} \cdot u(s) \tag{8}$$

The time delays are found visually, while the process gains, time constants and damping coefficients are found by applying

$$K = \frac{\lim\limits_{k \to \infty} y_k - y_{k=0}}{U} \qquad \text{(process gain)} \tag{9}$$

$$\hat{\tau}_1 = \arg\min_{\tau_1} \sum_k e_k^2 \qquad \text{(time constant, first-order model)}$$

$$[\hat{\tau}_1, \hat{\zeta}] = \arg\min_{[\tau_1, \zeta]} \sum_k e_k^2 \qquad \text{(time constant and damping coefficient, second-order model)}, \tag{10}$$

where $y_{k=0}$ is the initial output value, U is the step input size, and e_k is the error between the simulated model output and the output on file, at time k.

A first-order model is preferred whenever the fit of the second-order model is only negligibly[1] better. The transfer matrix is found to be:

$$\begin{bmatrix} y_w \\ y_a \\ y_c \end{bmatrix} \tag{11}$$

$$= \begin{bmatrix} \frac{0.1020}{(169s+1)} e^{-50s} & \frac{0.5583}{(1831s+1)(617s+1)} e^{-50s} & \frac{2.7726}{32^2 s^2 + 2 \cdot 0.5 \cdot 32s + 1} e^{-12s} \\ \frac{-0.0221}{31^2 s^2 + 2 \cdot 0.5 \cdot 31s + 1} e^{-35s} & \frac{0.7051}{(1867s+1)(549s+1)} e^{-40s} & \frac{1.6916}{119^2 s^2 + 2 \cdot 0.37 \cdot 119s + 1} e^{-12s} \\ \frac{0.0013}{(203s+1)} e^{-20s} & \frac{0.020}{(1826s+1)(623s+1)} e^{-20s} & \frac{-0.1455}{(301s+1)} e^{-7s} \end{bmatrix} \begin{bmatrix} u_t \\ u_f \\ u_r \end{bmatrix}$$

N4SID subspace method   The "Numerical algorithms for Subspace State Space System IDentification" method (N4SID) belongs to the subspace system identification family (Van Overschee & De Moor 1996). The method is an integrated part of the System Identification Toolbox for use in Matlab (Ljung 1997). The data are pretreated by centering and scaling before entered into the N4SID function.

The input signals are filtered PRBS's (Pseudo Random Binary Signals). Based on the observed RMSE (root mean square error) for various model orders, we chose to concentrate on a 7th order model and a 28th order model for the comparison with other models.

DSR subspace method   The "combined Deterministic and Stochastic system identification and Realization" method (DSR) also belongs to the subspace system identification family (Di Ruscio 1997). The method and software (Di Ruscio 1996) are easy to use, requiring only the data and one parameter to be specified. A singular value plot is supplied for helping to determine the model order. When the model order is specified, the program returns a state-space model (including the Kalman filter gain matrix, and the innovations covariance matrix) along with the initial conditions. The data are pretreated by centering and scaling before entered into the DSR program.

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[1] That is, when the difference in RMSE is zero for a rounded three digit number.

The input signals are the same filtered PRBS signals as were used for the N4SID algorithm. We chose to concentrate on a third-order model and a 7th order model for the comparison with other models.

Prediction error method (PEM) The prediction error method (Ljung 1999) (Söderström & Stoica 1989) is an integrated part of Matlab's System Identification toolbox (Ljung 1997). It offers a vast amount of possibilities regarding linear model structures, such as ARMAX, BJ, FIR and state-space models. However, for MIMO (multi-input multi-output) systems, the ARMAX-type of models get complicated and they are perhaps not very suitable for such systems. The state-space model is therefore often preferred for representation of MIMO systems.

Unlike the subspace methods, the PEM is an iterative method, based on minimization of the prediction error. The fact that it is iterative limits the possible number of free parameters in the model structure dramatically, and one should not expect to be able to identify high-order models (even when one is using a canonical form). A recommended method (Ljung 1997) for identifying MIMO models is to use a subspace method (such as N4SID or DSR) to identify an initial model, and use the parameters of this model as initial values for the PEM method. This approach is taken here, although the 7th and 28th order models were not improved by the PEM method, probably due to too many free parameters involved. However, the third-order DSR model where slightly improved by the PEM method.

3.4   Comparison of the models

Without change in operating condition New input signals were designed and applied to the full scale model. The levels of the input signals are such that the overall operating condition of the paper machine is in the neighborhood of the condition at the time of identification.

The RMSE's (see Equation 6) for the empirically identified and reduced mechanistic models are given in Table 1.

The PEM, DSR and N4SID models have good prediction[4] abilities, although the RMSE's have increased significantly as compared to the identification. The prediction abilities of the mechanistic models are in general good. The higher order mechanistic models have very good prediction abilities

With change in operating condition Yet another set of input signals were designed, differing from previously used signals such that the overall operating condition of the paper machine is changed. The change in operating condition include e.g. an increase in thick stock flow from around $370\,l/s$ to about $436\,l/s$, an increase of about

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[2] TM - Transfer Matrix (Equation 11). Time delays are not included in model order.

[3] Optimized.

[4] The $\hat{y}$'s are the simulated response from the deterministic part of the identified model, thus the phrase "prediction ability" does not mean that e.g. a Kalman filter is applied in the validation process.

Table 1: Root Mean Square Error (RMSE) for reduced and identified models. The operating condition is comparable to that at the time of identification.

Method	Order	$RMSE_{weight}$	$RMSE_{ash}$	$RMSE_{conc.}$
TM[2]	15	0.30	0.16	$3.9 \cdot 10^{-3}$
PEM	3	0.16	0.10	$3.46 \cdot 10^{-3}$
DSR	3	0.17	0.12	$3.79 \cdot 10^{-3}$
DSR	7	0.13	0.098	$3.70 \cdot 10^{-3}$
N4SID	7	0.14	0.10	$3.37 \cdot 10^{-3}$
N4SID	28	0.11	0.063	$2.45 \cdot 10^{-3}$
Mech.[3]	38	0.12	0.061	$1.91 \cdot 10^{-3}$
Mech.	38	0.16	0.091	$2.65 \cdot 10^{-3}$
Mech.	87	0.077	0.027	$1.00 \cdot 10^{-3}$
Mech.	161	0.041	0.017	$0.52 \cdot 10^{-3}$

Table 2: Root Mean Square Error (RMSE) for reduced and identified models. The operating condition is different from what was used for identification.

Method	Order	$RMSE_{weight}$	$RMSE_{ash}$	$RMSE_{conc.}$
TM[2]	15	0.30	0.14	$4.08 \cdot 10^{-3}$
PEM	3	0.19	0.14	$3.42 \cdot 10^{-3}$
DSR	3	0.22	0.18	$4.97 \cdot 10^{-3}$
DSR	7	0.18	0.14	$3.27 \cdot 10^{-3}$
N4SID	7	0.18	0.14	$3.16 \cdot 10^{-3}$
N4SID	28	0.16	0.10	$2.31 \cdot 10^{-3}$
Mech.[3]	38	0.12	0.052	$1.61 \cdot 10^{-3}$
Mech.	38	0.12	0.066	$1.91 \cdot 10^{-3}$
Mech.	87	0.075	0.032	$0.86 \cdot 10^{-3}$
Mech.	161	0.047	0.016	$0.53 \cdot 10^{-3}$

90% in filler added to the short circulation, an increase of about 50% of retention aid and an increase in machine velocity from $1500\,\mathrm{m/min}$ to $1650\,\mathrm{m/min}$.

The input signals are shown in Figure 3, and the RMSE's (see Equation 6) for the empirically identified and reduced mechanistic models are given in Table 2.

The PEM, DSR and N4SID models are identified at a different operating condition, and thus it is not a surprise that the prediction ability is decreased (except for some of the y_c outputs, for which the ability has improved). The mechanistic models are producing better predictions than previously (with a few exceptions).

Figure 4 shows the responses from the full scale model and the third-order DSR model.
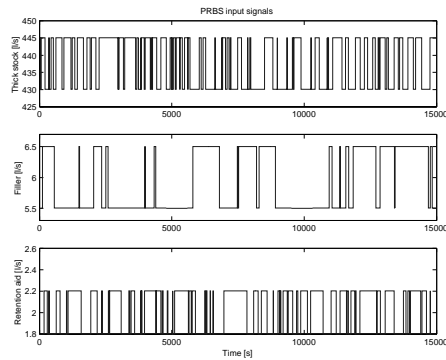
Figure 3: The filtered PRBS signals used for validation of the models. The overall operating condition of the paper machine is different from what was used for model identification and reduction.
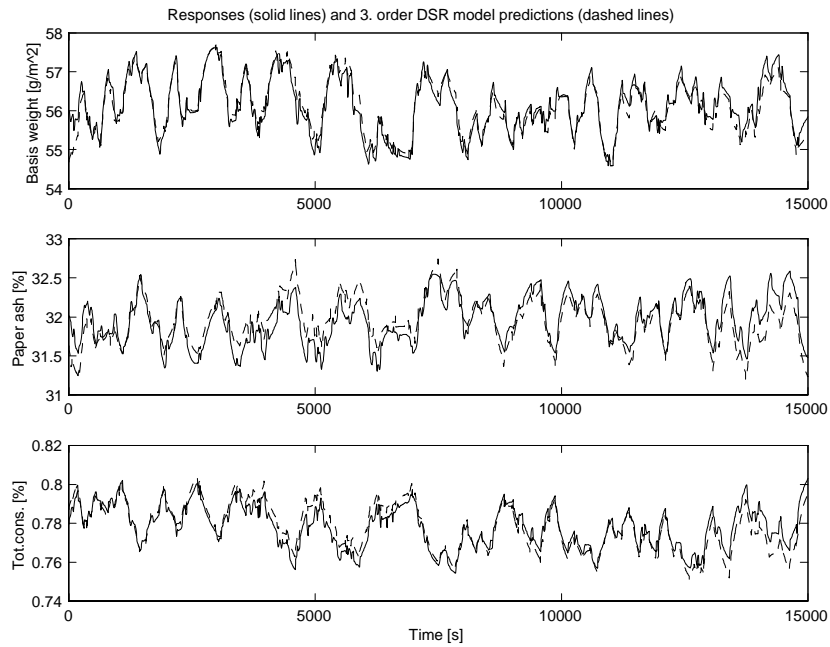

Figure 4: Full scale model responses (solid lines) and third-order DSR model responses (dashed lines), after change in operating condition.

4 Modeling and identification from real-time data

In Section 3, mechanistic models and empiric models of various orders and complexity were compared. In this section we will study some of the same concepts with real-time data. However, we confine ourselves to study empiric models. Fitting of mechanistic models to real-time data is more time consuming and is saved for future work.

4.1 Experiment design

One data set for identification and one data set for validation were collected. The type of experiments performed on the simulation model in Section 3 are impossible in reality, because step changes of a valve opening or a pump velocity are physically impossible. An approximation of the filtered PRBS signal is possible by changing the setpoints of the mass flows according to a PRBS scheme and let the valve and pump controllers work out the correct openings and velocities. However, on a paper machine even such an experiment is performed with high risk of poor paper quality or even sheet breaks. A solution to this problem is to perform closed loop experiments, i.e. in this case experiments where the basis weight, paper ash and wire tray total consistency controllers are in automatic mode. There is a vast amount of published material on closed loop system identification, and various approaches and algorithms are treated in more detail in e.g. (Ljung 1999), (Söderström & Stoica 1989) and (Forssell 1999). Our approach is the recommended one and it is often called "the direct approach" (Ljung 1999). In the direct approach we use the process inputs u and outputs y in the same way as for open loop identification, ignoring the feedback mechanisms and the reference signals.

Figure 5 shows the experimental plan with the changes in setpoints that the process operators should follow.

Figure 6 shows the resulting real-time input signals which is used together with the collected output signals for validation of models. Thus, the experiment plan gives filtered PRBS signals for the reference values, but only the process inputs (u) and outputs (y) are used for identification.

A similar procedure is used for collecting the identification data set.

4.2 Identification methods and closed loop data

It is well known that closed loop identification with the direct approach and a prediction error method (PEM) works very well (Ljung 1999), (Forssell 1999), (Söderström & Stoica 1989). However, problems may arise for poorly excited systems (this is also the case for open loop identification) and for systems with too simple controllers. The standard example of a closed loop identification failure uses a single-input-single-output ARX model with a proportional controller and with the reference value set to zero. This system is not identifiable in closed loop.

For subspace methods it is a fact that when applied in a straightforward fashion they do not yield consistent estimates in closed loop. This is due to the fact that the property of uncorrelated noise and system inputs is a basic assumption in these
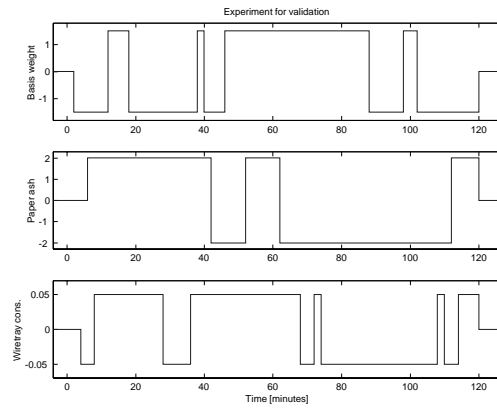
Figure 5: Experiment plan for the PM6 process operators. The plan shows the changes in setpoints for the validation data set.
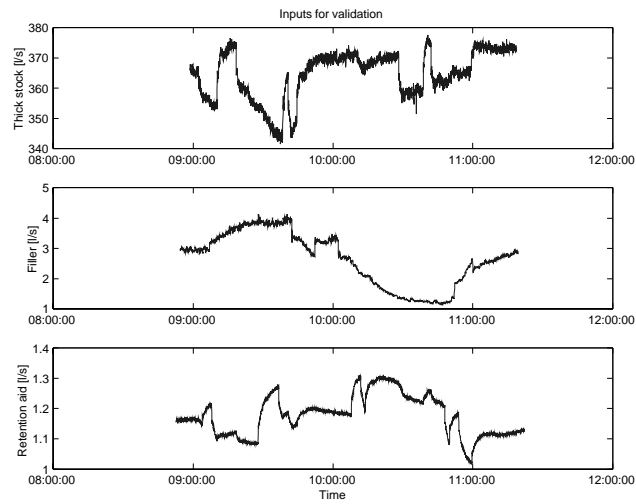

Figure 6: The resulting input signal with the experiment plan of Figure 5.

Table 3: RMSE values for third-order DSR model.

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

algorithms. As pointed out by e.g. (Forssell 1999) it is possible to use the reference signal instead of the input signal in the projection matrix which may cause problems in closed loop. However when using the subspace software packages in a straightforward fashion, a bias is introduced due to the correlation between noise and inputs. In practice this may not be a problem, due to the fact that all consistent system identification methods rely on several assumptions that do not hold, e.g. that the model structure equals the real structure. The question is to what extent a closed loop experiment invalidates the assumption of no correlation between noise and inputs, and to our knowledge there exist no results on this matter. However, it seems intuitively correct that the larger the signal-to-noise ratio is, the more insignificant is the closed loop problem. This is due to the fact that the correlation between noise and inputs will decrease with larger signal-to-noise ratio. Studying figures of inputs and outputs from experiments is perhaps the easiest way (perhaps not the most scientific way) of judging the size of the signal-to-noise ratio. In our case, the signal-to-noise ratio seems quite large, and subspace methods will be used along with the prediction error method.

4.3   Results

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 (centering may also be done by other methods, e.g. subtracting the mean of the series), 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.

An RMSE (root mean square error) criterion, as in Equation 6, was used for comparing the identification and validation of the various models.

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 7, and Table 3 gives the RMSE values.
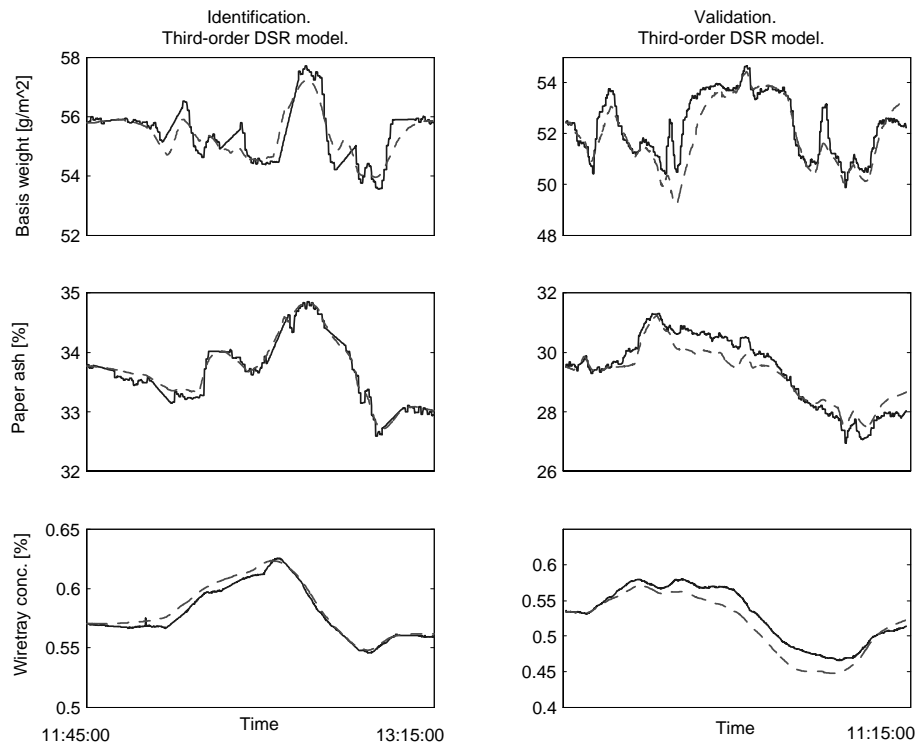
Figure 7: Real data (solid lines) and simulated data (dashed lines). Data set for identification collected at September 19. 2000, and data set for validation collected at October 27. 2000. Identification was carried out on centered data.

With N4SID we identified a fifth-order centered and scaled model, in addition to several higher order models (11th to 23rd 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 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.

5 Calibration for estimation of quality variables

System structure   Section 3 and 4 focus on various models for control. For these models we assumed that both the (controllable) inputs and outputs are measured, and are therefore known. A problem within the paper industry is that some of these measurements are lost when sheet breaks occur, and a standard solution to this problem is to "freeze" the corresponding inputs at their present values (the values at the time of the sheet break). This strategy will in most cases lead to drifts in e.g. headbox and white water consistencies. It seems more appropriate to estimate the missing measurements and Figure 8 shows how this may be arranged.
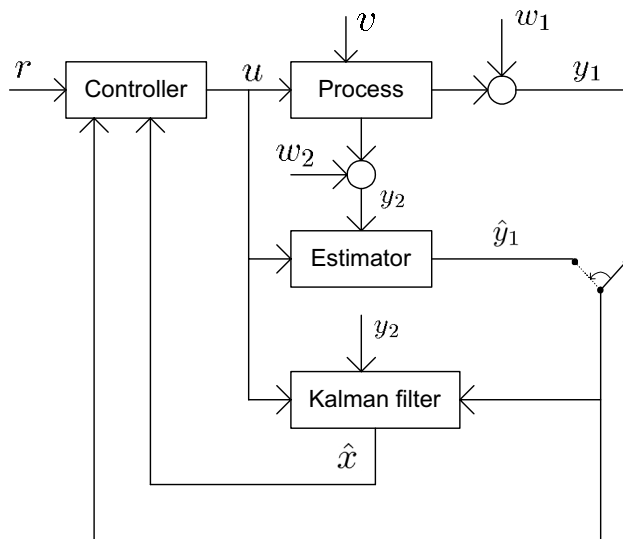

Figure 8: Arrangement for estimating missing measurements during sheet breaks.

In Figure 8 a distinction has been made between the primary y_1 outputs, which

Table 4: RMSE values for OE and DSR models.

	$RMSE_{weight}$	$RMSE_{ash}$
DSR	0.4123	0.3840
OE	0.3691	0.3504

correspond to the basis weight, paper ash and wire tray total consistency outputs, and secondary y_2 outputs which are used as inputs to the estimator. The secondary outputs are the wire tray filler consistency, the headbox total and filler consistency and the thick stock total and filler consistency. Note that for simplicity Figure 8 does not take into account that one of the primary outputs (the wire tray consistency) is available and used as estimator input even during sheet breaks. Whenever a sheet break occurs the primary measurements y_1 are replaced by estimates $\hat{y}_1$. The measurements or estimates are fed to the Kalman filter and the controller. The controller arrangement consists of e.g. model predictive control (MPC) and some single loop controllers (SLC) as further discussed in Section 6.

In Figure 8 the estimator and Kalman filter are represented by separate boxes. This is based on the assumption that the estimator is identified from process data with the aim of obtaining the best possible $\hat{y}_1$ estimates, while the Kalman filter is based on a mechanistic model with the aim of obtaining the best possible state estimates $\hat{x}$ for control purposes. The best $\hat{y}_1$ estimates will in fact be obtained by use of two separate estimators, one for each of the primary measurements that will be lost at a sheet break.

Estimator identification   The estimators can be identified by use of a prediction error or subspace method using both the manipulated inputs u and the secondary process outputs y_2 as estimator inputs. Assuming a well known mechanistic process model, including noise covariances, the optimal estimator would be a Kalman filter driven by u and y_2 but not by y_1 (which is not available when the estimator is needed). This implies that an output error (OE) model structure should be specified for the identification, which can readily be done in the prediction error method (Ergon 1999b). It further implies that a direct subspace method (e.g. DSR) that make use of past y_1 values as estimator inputs will give theoretically non-optimal results, although the difference between OE and DSR results may not be of much practical importance.

Different identification methods have been tested by use of a mechanistic model similar to the one presented in Section 3, and noise covariances adjusted to achieve realistic output noise as compared with process measurement data (Forsland 2000). The estimator validation RMSE results were as given in Table 4, showing differences in line with the theoretical discussion above.

Figure 9 shows the validation responses for the paper weight based on a first-order OE estimator in the bracketed time period (from sample 20 to sample 320) and a first-order DSR estimator before and after this time period. Figure 10 shows the corresponding results for the paper ash content. A further investigation of this based on real data is part of the future work.
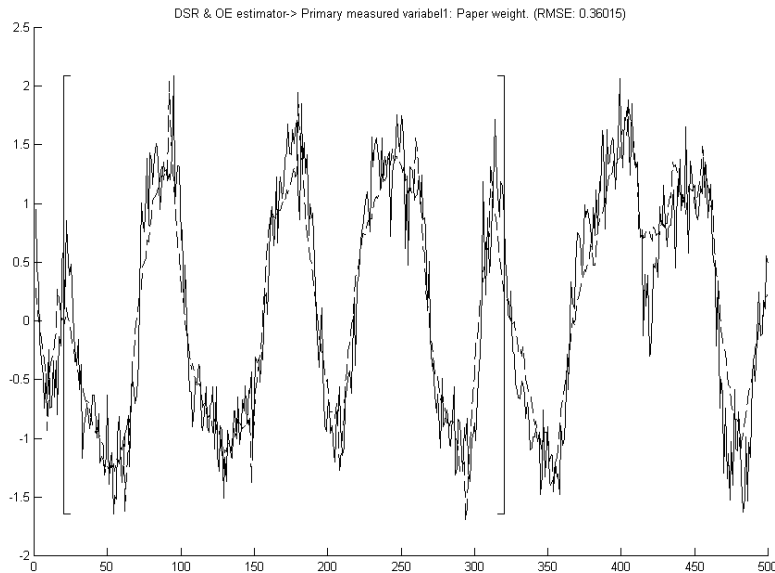
Figure 9: Basis weight. Mechanistic model output as solid line and estimator output as dashed line. First-order OE estimator in bracketed time period and first-order DSR estimator elsewhere. The data are centered and scaled.

Estimation based on multirate sampling data The primary output measurements are obtained with a lower sampling rate then the rest of the process signals, due to the scanner based sensor. The OE estimators may be identified also in this case, although some modifications of the Matlab identification functions are necessary (Ergon 1999a). A further investigation of this based on real data is also a part of the future work.

6   Control structure and related work

When a suitable model has been developed (possibly identified) it will be used in conjunction with model predictive control (MPC). MPC refers to a class of algorithms that compute a sequence of manipulated inputs in order to optimize a chosen criterion. The details of MPC algorithms are not discussed any further in this paper, and the interested reader is referred to e.g. (Camacho & Bordons 1999) or (Lie 1999). The interest in MPC has increased significantly since its introduction in the 1970's, and (Qin & Badgwell 1997) give an overview of commercial industrial solutions and implementations. The pulp and paper industry has also several reported MPC implementations, e.g. (Qin & Badgwell 1997) and (Lang et al. 1998).

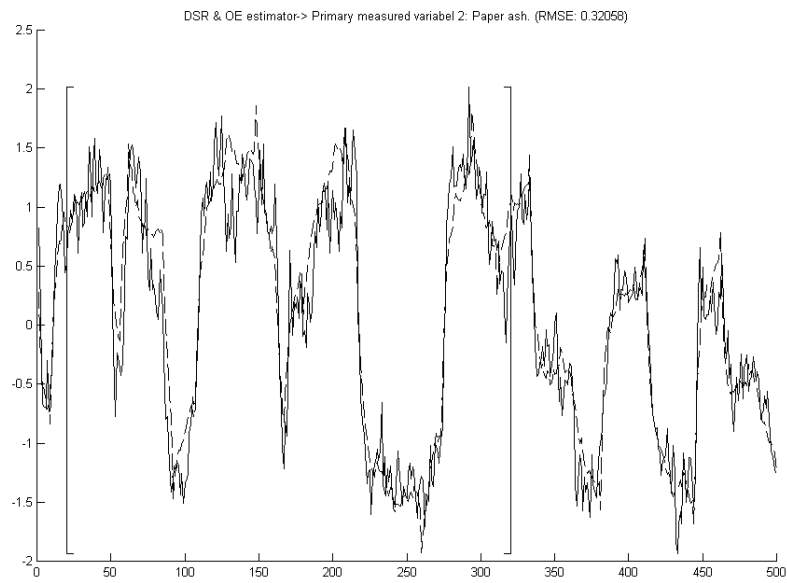A model structure has to be selected for the MPC, and commercial packages based

Figure 10: Paper ash. Mechanistic model output as solid line and estimator output as dashed line. First-order OE estimator in bracketed time period and first-order DSR estimator elsewhere. The data are centered and scaled.

on e.g. impulse response models, step response models, state space models and others are known to exist (Camacho & Bordons 1999). The development of a mechanistic model and the use of subspace identification techniques leads to state space models, and such models may be used in the MPC at PM6. An overview of the control structure is given in Figure 11.
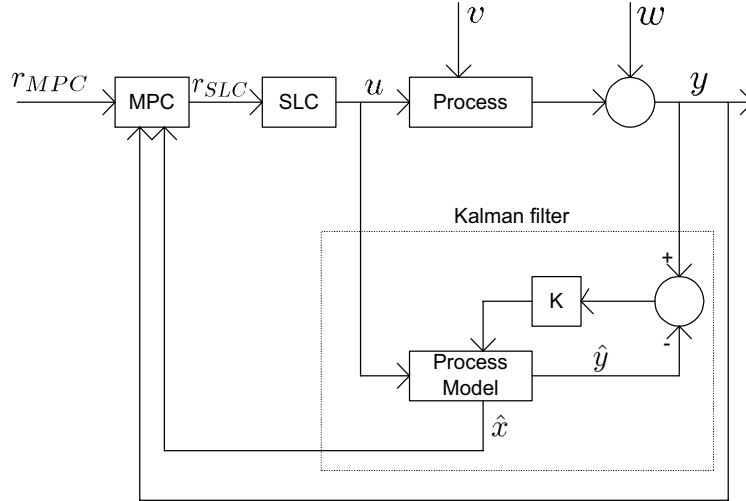

Figure 11: MPC and Kalman filter structure.

Here, a Kalman filter has been added for estimation of internal states that are not measured. In the figure, we use the abbreviation SLC for single loop controllers operating on the valves and pumps. Estimated states and outputs are $\hat{x}$ and $\hat{y}$ respectively. The following vectors are used:

$$r_{MPC} = \begin{bmatrix} r_{weight} \\ r_{ash} \\ r_{conc.} \end{bmatrix}, r_{SLC} = \begin{bmatrix} r_{thick\ stock} \\ r_{filler} \\ r_{retention\ aid} \end{bmatrix}$$

$$u = \begin{bmatrix} u_{thick\ stock} \\ u_{filler} \\ u_{retention\ aid} \end{bmatrix}, y = \begin{bmatrix} y_{weight} \\ y_{ash} \\ y_{conc.} \end{bmatrix}$$

Disturbances, v and w   The mechanistic model which is developed and the empiric models which are identified can never cover every aspect of the process. The underlying physical phenomena are far too complex, and in many cases not known at all. It is therefore instrumental that those mechanisms that are not modelled but still affect the outputs, are not allowed to invalidate the model. Such phenomena are typically present in the process- and measurement noise v and w (see Figure 11).

At Saugbrugs several efforts focusing on these disturbances are initiated. A short description of the most prominent efforts will be given next.

Thick stock stabilization   A sixth-order mechanistic model of the thick stock, including the mixing and machine chests, is developed and used for controlling the filler consistency. A Kajaani RMi measuring device for on line filler consistency measurements is installed and has been used for validation of the controller performance. The controller operates in a feedforward fashion, relying on the model and measured inputs only. The controller is working very well, although it is not operating in closed loop.

A feedforward controller which utilizes the measured total consistency between the mixing and machine chests, and compensates for any deviation from the setpoint by altering the speed of the thick stock pump, is also implemented. The feedforward controller is based on a dynamic model of the machine chest.

Charge measurement and control   A project including Kemira (supplier of retention aid at PM6) and Neles Automation is initiated for, amongst others, investigating the need for measurement and control of charge. A Kajaani CATi measurement device is installed, and is currently being connected to the control system. One reason for this particular project is that it has been observed that in order to control the wire tray consistency the amount of retention aid often varies with ±15% at normal and stable conditions. Problems in the wet end when changes in the dosage of bleaching chemicals occur are often observed and are probably related to the charge of the stock. A cationic coagulant will be used for controlling the charge if the project concludes that this is beneficial.

pH variations and control   Some variations in pH are observed, notably from about 4.4 to about 5.0. The models from Section 3 and 4 will be implemented in the control system, and on-line simulations in parallel with the process will show whether these variations in pH invalidate the models. Some preliminary investigations on control of pH has begun.

Air measurement and control   A project for investigating the need for air measurement and control is (temporarily) finished, with no air found in the headbox. It may be interesting, at a later stage, to measure and control the air content in the headbox by acting on the amount of defoamer added to the white water tank.

Calibration of measurement devices   An intensified calibration program is initiated, focusing especially on consistency measurement devices.

7   Conclusions

Various aspects of the project "Stabilization of the wet end of PM6" at Norske Skog Saugbrugs, Norway, are presented in this paper. The basic idea of the project is to use model predictive control (MPC) to achieve the objects of reducing the down time and reducing the variability in selected key variables. In the model structure, the chosen inputs are the thick stock pump, the addition of filler in the short circulation, and the addition of retention aid at the screens. The outputs are the basis weight, the paper ash content, and the wire tray concentration.

A 528 order mechanistic model is developed and an overview is presented. A lower order model is more beneficial for control purposes and model reduction and system identification techniques are used to arrive at several lower order models. These models are compared for their accuracy with respect to the full scale model (the 528 order model). Linear low order empiric models showed in general good accuracy, although depending on the operating condition of the paper machine. The reduced order mechanistic models are nonlinear and of higher order than the empiric models. The accuracies of these models were in general good and not depending on the operating condition of the paper machine.

Empiric models were also identified from real time data. Experiments were carried out in closed loop and subspace and prediction error methods were used for the identification. A third-order model (identified with the DSR subspace method) gave good accuracy at validation, and no higher order models were significantly better. For the validation, the operating condition of the paper machine were somewhat altered compared to the operating condition at the time of identification.

A solution to the problem of missing measurements during sheet breaks is proposed. One estimator for each of the measurements that are lost is identified, and at sheet breaks the estimate replaces the corresponding output. The estimator is based on an output error (OE) model structure and an underlying Kalman filter, and it utilizes other measurements as estimator inputs. Simulation results, with first-order estimators, are in line with the theoretical result that the OE model structure is the optimal one for these estimators.

A possible future model predictive control (MPC) structure is presented. It is vital that those mechanisms that are not modelled are not allowed to invalidate the model so that the MPC fails. A range of projects aiming at rejecting disturbances are established, focusing on thick stock stabilization, charge, pH, air, calibration routines, and more.

It is expected that the work on model reductions, model validation and identification of estimators will go on for a few months, and that a preliminary MPC controller will be implemented in 2001. The project at PM6 will run throughout 2002.

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