

# Optimized on-line process control of bleaching operations with OPTCAB

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To produce pulp for paper production or as market pulp is a complicated on-line process with many integrated stages that impact the final quality. In the bleaching plant which is at the end of pulp production, the main objective is to increase pulp brightness within specified limits. Here chemical treatments are applied in sequential stages to achieve the right brightness while striving to maintain the pulp strength as unaffected as possible. The raw material, i.e. pulp logs and wood chips from saw mills, differ in quality and properties. Due to this, it is important to continuously update the amount of chemicals added to the pulp in real-time. This is typically done by experienced operators. In this paper, we describe an on-line optimization based decision support system called OPTCAB that controls the bleaching process at Billerud AB's paper mill in Skärblacka. The solution approach is based on two phases. In phase one, we establish approximations of each of the processes based on process data collected on-line. These approximations are found by solving a set of constrained least square problems and are updated every 15 minutes. In phase two, we formulate an overall nonlinear control problem that links all stages together and aims to minimize the cost of chemicals. This is solved on-line every five minutes. The system has been in operation during the last three years providing a 10% reduction in the use of chemicals. Additional benefits include a more stable brightness quality.

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## 1. Introduction

The pulp and paper industry produces a large number of paper and other cellulose based fibre products. The total quantity of cellulose-based products consumed every year world-wide exceeds 360 million tonnes. Newspapers, copy paper, various types of tissue, bottle labels, cigarette papers, and coffee filters are just a few examples of products regularly used in our everyday life. The pulp and paper industry is a very important sector for many countries. For example, Sweden is the world's fourth largest export country of pulp and paper, and the second largest export country for sawn timber. The total export value corresponds to 15% of the Swedish gross national product, and the forest industry employs 185,000 people. In monetary terms the export value relates to about 12 billion euros. In 2005 there were 60 paper and pulp mills in Sweden, and they produced 11 million tons (metric) of paper and 4 million tons of market pulp.

To produce pulp (for paper production or as market pulp) is a complicated process with many integrated stages that impact the final quality. The capacity utilisation in the business is generally very high and pulp and paper companies normally run continuously except for regular maintenance stops. The raw material, i.e. pulp logs and wood chips from saw mills, differ in quality and have different properties due to species, age classes, moisture content, storage time, etc. This article will focus on the bleaching plant, which is at the end of the pulping process and thus is the last opportunity to ensure that the quality of the pulp is correct.

The main aim of the bleaching process is to increase pulp brightness by removing or modifying the light absorbing substances that remain in the pulp after it has been boiled and washed. Chemical treatments are applied in sequential stages to achieve the right brightness while still maintaining the strength of the pulp. Maintaining stable pulp quality is a difficult task and the commercial plant systems usually require manual bleaching control by experienced operators. Competition on the world pulp market is fierce. It is therefore crucial that pulp production is cost-effective. The chemical cost of bleaching is normally between 25 and 35 Euros per metric ton and any percentage savings involve large benefits and improved environmental impact.

The bleaching process involves several stages and many properties such as brightness, kappa number and pH-value to mention just a few. Each of these properties needs to be measured and monitored. The process control is to decide on-line chemical charges in each of the stages. There are a number of practical restrictions of the properties and a target quality (and limits) of the final brightness before it reaches the paper machine. Even though the operators are very skilled, they tend to add more chemicals than they need to overcompensate for earlier decisions. This often leads to an oscillating behavior, which in turn increases chemical costs and environmental impact. Also, because of the long time (typically 8-12 hours) which the bleaching process takes, decisions made by one operator have an impact late in the next operator's shift. However, different operators have different skills and individual strategies in their process control. When the properties of the wood chips change, there are sometimes substantial problems before the operators get the situation under control again.

There are many articles describing the properties of the pulp when it is mixed with different chemicals under various operating conditions. Typical articles in this area are for example Lopez et al. (2003) who describe how hydrogen peroxide can be used and how it affects the bleaching of the pulp and Valchev et al. (2005) who describe different options and their effectiveness in bleaching pulp. However, there are few articles which describe process control systems for the overall bleaching process. Castro and Doyle (2004b) introduce a benchmark problem of a pulping process, including both the fiber line and the chemical recovery area. The problem is described with a set of partial differential equations. Later, Castro and Doyle (2004a) introduce a heuristic for the design of plant wide control strategies and apply the heuristic to the benchmark problem. Two control strategies (decentralized control and a unit-based model predictive control) are compared according to their capacity to reduce total error and maximize operating profits. The control strategies are studied through closed-loop simulations of the process in a number of process steps. VanBrugghe et al. (2004) applied a real-time optimization to the same benchmark. The solution was obtained with a modified version of an IMC-based (Internal Model Controller) optimization method. It uses an approximate model of the process to simplify and accelerate the minimization process. The total cost of the bleaching section was reduced by 10.6%. The approach was to update operators set-points every 400 minutes. Keski-Säntti et al. (1999) optimize the control of a bleach plant by using neural networks. However, they do not give any indication of possible savings using that method. Lampela and Erkkilä (1999) describe how to achieve and maintain a high pulp quality and optimize chemical costs by selecting the chemicals used. They also discuss the importance of reliable on-line information and how artificial intelligence can be used as the basis of the process control. There are also papers describing longer term planning issues in the pulp and paper industry. Scheduling and production planning models and methods are found, for example, in Bredström et al. (2004) and Keskinocak et al. (2002). Shah (2005) discusses advances in and challenges for the general process industry supply chains.

One contribution of this article is the development of a general and robust solution approach to the bleaching process. The solution approach is designed to always produce robust solutions even though the data is of low quality or even faulty. It comprises of two phases. First we use process data collected on-line over the previous days to establish a detailed description of the underlying

processes. This is the identification problem and the description consists of a set of approximate functions found by solving constrained least square problems. The identification problem is resolved every 15 minutes to ensure an accurate description of the current operational situation. Second we use these approximations to formulate an overall nonlinear control problem where the stages are integrated and the cost of chemicals is minimized, subject to certain operating conditions and targets. The process control problem is resolved every five minutes. Special care is taken to remove faulty data and provide a robust on-line solution.

A second contribution is the implementation of the system OPTCAB and to present the results and experiences reported from this. The system was developed and tested during the period 2001-2003 at Billerud AB's paper mill in Skärblacka, Sweden. The mill has three pulp lines, four paper machines and a pulp drier. The mill has 620 employees and produces sack and kraft paper with an annual production capacity of 250,000 tons. Furthermore, it produces fluting and market pulp with an annual production capacity of 90,000 tons and 70,000 tons, respectively. OPTCAB has been in full operation since 2004 and experience shows that it provides several benefits. The savings in the use of chemical has decreased by about 10% compared with manual control. The final brightness quality is more stable and lies within preferred limits. Moreover, the operators now have more time for other development and analysis work.

The structure of the paper is as follows. In Section 2 we describe the bleaching process and the control problem. In Section 3 we describe the models and methods used to formulate and solve the identification and control problems. In Section 4 we describe the implementation of the OPTCAB system. Thereafter in 5 we provide some results from the system components and of experiences from the use of the system. Finally we make some concluding remarks.

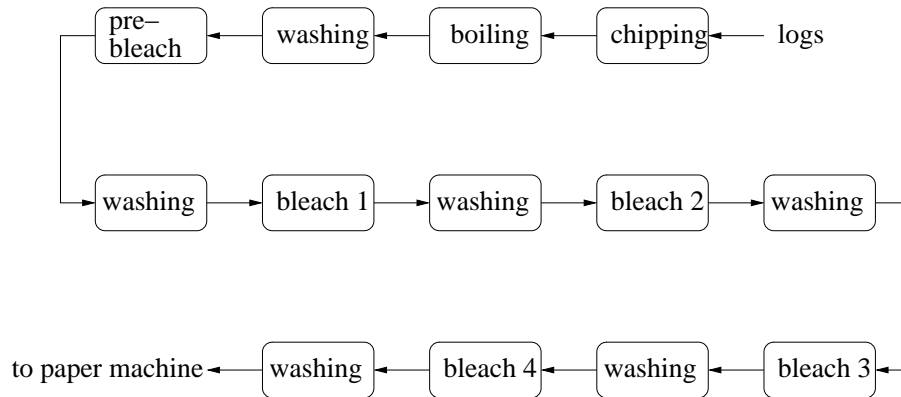
## 2. Problem description

The desired properties for different types of paper vary. In tissues, for example, softness is often the most important feature. In the case of toilet rolls, softness should be coupled with a high strength. Softness can be achieved with a high degree of short-fibre pulp (e.g. Eucalyptus), but in order to get the strength, a certain degree of long-fibre is needed. However, it is important that the long fibres are flexible, as this allows the pulp both to maintain the quality of softness and gives reinforcement. This type of long-fibre properties can be found in Spruce (*Picea abies*) harvested in thinnings. Other papers, such as paper sacks, calls for a high tear strength. This property can be achieved by using a high content of long-fibre pulp based on residue wood from lumber production (e.g. Spruce chips). The reason for this is that sawmill chips come from the "surface" of the logs used in the lumber production, where the fibres are longest and have the thickest walls.

The bleaching of pulp is a multistage process. This is illustrated in figure 1. The first stage is to convert pulp logs from different species to chips and mix them according to recipes with sawmill chips depending on the pulp quality needed. In the second stage, chips are boiled and washed. Here, the fibers and lignin are separated. After this, there is typically a pre-bleaching step followed by washing. Next comes the main bleaching process which may consist of four bleaching stages, each followed by washing. The actual process is done in large bleaching reactors (so called bleaching towers), see figure 2. At each step, the pulp slowly moves through large tanks while the chemical reactions take place. The total bleaching time can be 8-12 hours which means long process delays. The operator can manually choose the chemical charges (one for each stage), and this requires experienced operators. Also, because of the long time span of the process, decisions made by one operator may impact later in the next operator's shift.

Bleaching reactions are non-linear by nature and various chemicals are used in the stages. Previous processes and wood species affect the fiber properties. There are several essential process variables and many of them interact with each other. Reaction conditions are important, and the main factors that affect these are chemicals, temperature, pH-value, pressure, concentration and

**Figure 1** Illustration of the pulp process. In this example the bleaching is performed in a pre-bleaching stage and four main stages.



**Figure 2** Photo of the bleaching towers used in the four stages at Billerud AB's paper mill in Skärblacka. Photo by Billerud AB.

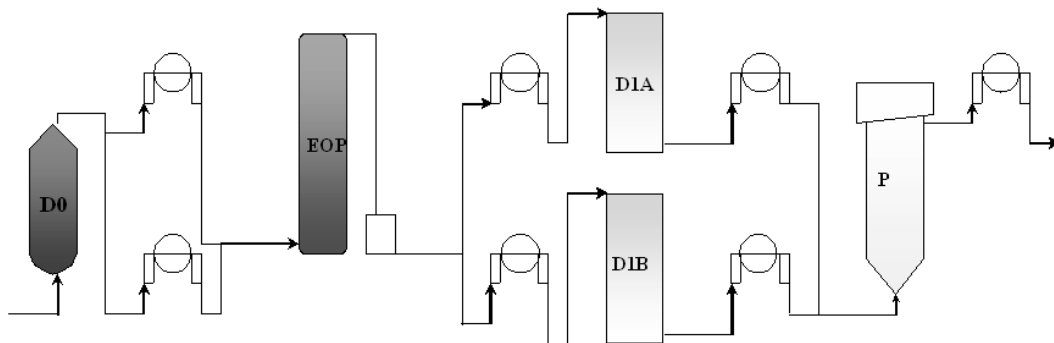


time. Production rate (or flow speed) is an important parameter because it affects the reaction times, process delays, and mixing efficiency as well as washing efficiency. Many of the properties are measured before and after each step, but some of the properties are only measured every 30 minutes or even more seldom, which together with potential sensor errors, makes information quality-sensitive. Additionally, the time between a chemical charge and the measured result can be up to five hours.

There are a number of goals and operational restrictions on the process control. The product quality targets include limits on some of the pulp properties during the process as well as the chemical charges. Common pulp properties that are limited are brightness and kappa number at different stages of the bleaching process. Moreover, the control should not change drastically between updates i.e. the control should be smooth and not have any bang-bang effects. Given these restrictions, the overall aim is to minimize the total consumption of bleaching chemical over all stages. This has both a positive economic effect and a positive environmental impact.

The bleaching process at Billerud AB's paper mill in Skärblacka, where the system has been developed is shown in figure 3. A simplified description of this project is given in Flisberg et al. (2005). The bleaching is divided into four stages plus a pre-bleaching step. The time for the pulp to pass through the system is about nine hours. In the first stage, Stage D0, the pulp is delignified in an acid environment using chlorine dioxide. Then there is an extraction stage, Stage EOP, where the alkali-soluble lignin is removed with sodium hydroxide, oxygen, and hydrogen peroxide in a chemically alkaline environment. In the last two stages, Stage D1 and Stage P, pulp brightness is gradually increased by dissolving lignin and eliminating the chromophoric groups in the lignin. This is done in an acid environment with chlorine dioxide in Stage D1 and in a alkaline environment with hydrogen peroxide in Stage P. In Stage D1, the pulp goes through one of the towers, D1A or D1B. Approximately half of the production goes through each of the towers.

**Figure 3** The bleaching process used at the paper mill in Skärblacka. The pre-bleaching is done just before stage D0.

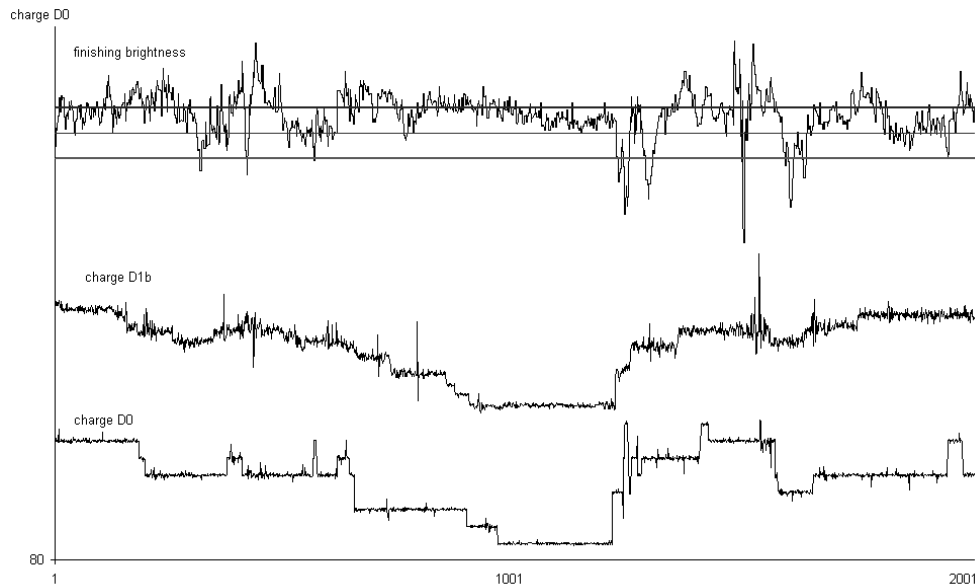


The mill has upper and lower brightness limits after each of the stages in the process, and in particular after stage P. The mill also requires some residuals of chlorine dioxide after the stages D0 and D1 to avoid brightness reversion. In figure 4, we illustrate the manual control in stage D0 and D1B and the resulting brightness after stages P over a period of 17 days. The central line for the final brightness is the target and the two other lines indicate the limits. It is clear that the average brightness is above the target and that it is often outside the set limits.

If a target value after each stage is set, then a combination of feed-forward, feed-back and ration control loops can be used to control the system and no optimization is needed. However, the optimal target values will vary depending on the properties of the pulp when it reaches the bleaching phase. Therefore it is important to have a system that changes the level of bleaching "work" that is done in each stage. It is possible to gain considerable savings in chemical consumption if the chemical loads and the disturbances can be divided optimally between each of the bleaching stages.

The objective with the development for Billerud AB's paper mill in Skärblacka is to develop a decision support system to control all the main chemical charges in the bleach plant. This is to decrease the total cost of chemical consumption subject to meeting the product quality targets. Other quality targets are that the process control does not oscillate and is not too different to a manual control (otherwise the operators might overrun the automatic process control). With the system and with a good data quality from the measurements we can also provide more flexible restrictions for the quality after each stage. This means that the control problem can better change the bleaching work in the different towers (or stages). Since the control is used on-line, the solution to the control problem must always be a usable control. This must be possible despite potential problems of faulty data.

**Figure 4** Example of manual operation over a period of 17 days. Upper: Brightness after stage P. Middle: chemical charge of chlorine dioxide in stage D1B. Lower: chemical charge of chlorine dioxide in stage D0.



### 3. Models and methods

#### 3.1. Overall solution approach

The main idea behind OPTCAB is to combine flexible and conservative process models with robust optimization. The solution approach is first to determine approximate functions for the process models describing behavior of each of the bleaching stages. These approximate functions are used in a second step where the overall control problem is formulated and solved i.e. what amount of chemicals that should be added in each stage for the pulp (plug) entering the process. A similar approach has been used in the refinery industry by Fransiska et al. (1997). In this paper, approximate functions are used to describe the refinery processes in oil crude distiller units in order to optimize the costs in a refinery.

A process model for each bleaching stage is determined dynamically, i.e., it is continuously updated in accordance with the varying production and pulp quality. For each bleaching process, input, output and control (chemical charges) variables are defined. An approximate function describes the relationship between each output and all input and control variables. The structure of the approximate functions can be based on theoretical and/or empirical results for the bleaching process. In order to determine the process model, a set of parameters in the approximate functions must be computed. This is an identification problem and we formulate this as a least-square optimization problem with the parameters as decision variables. Extra constraints on practical restrictions are added to the model. As data, we use a set of historical process measurements.

To determine the data needed to formulate the process model, a plug flow model is created to track the movement of the pulp material through the process. This is done by using pulp tracking, assuming a pure plug flow behavior to account for varying delays in the different stages of the process as result of changes in production rate, tower levels, and pulp concentration. The model tracks the movement of stock through the towers as well as the state (properties) of the stock and chemical charges at the different stages of the process. This information is needed in order to relate correct input with the right delayed output. Normally some mixing takes place in the towers which means that the flow is not a pure plug flow but in practice, the mixing is often limited and can be ignored.

With the information gained from the process models, a control problem that integrates all the bleaching steps is formulated. In this model we use the chemical charges as control variables and input/output properties as unknown state variables. The objective is to minimize the cost of chemicals. As constraints we use:

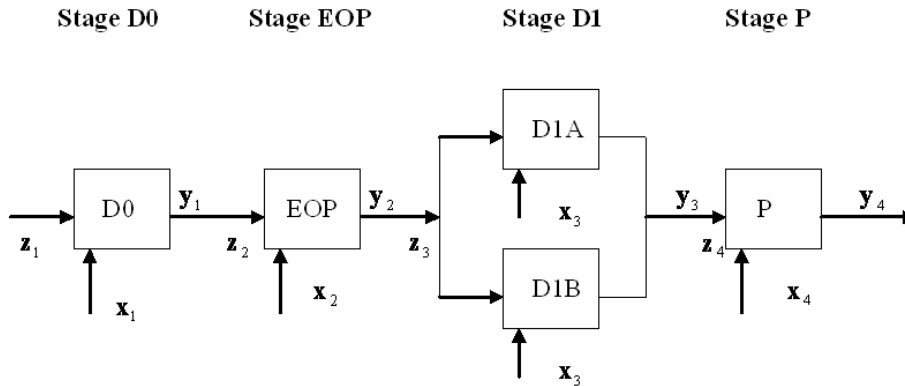
- the approximate functions (defined in the process models)
- linking constraints for input/output variables (between stages)
- lower and upper bounds on control variables
- lower and upper bounds on state variables.

As we have an on-line problem, we need to be particular careful about potential faulty data and the fact that we always need to provide a control solution. These considerations are closely related to the specific implementation and will be discussed in section 4.

### 3.2. Basic notations

We assume that the bleaching process has  $n$  stages. For each stage  $i$ , we define the output  $\mathbf{y}_i$ , given the state vector  $\mathbf{z}_i$ , and the control  $\mathbf{x}_i$  (chemical charges), see figure 5. The state vector  $\mathbf{z}_i$  corresponds to important properties of the pulp entering stage  $i$ , for example brightness, kappa number, temperature, residence time, and pH-value. The control  $\mathbf{x}_i$  corresponds to the amount of chemicals charged in stage  $i$ . The output  $\mathbf{y}_i$  gives state values of important pulp properties like brightness and kappa number after stage  $i$ .

**Figure 5** Illustration of stages and related state, control and output vectors used in the models.



For each stage  $i$ , we use a vector function  $\mathbf{P}_i = \{P_{ij}\}$  describing the output  $\mathbf{y}_i = \{y_{ij}\}$  as

$$y_{ij} = P_{ij}(\mathbf{z}_i, \mathbf{x}_i) \quad (1)$$

Theoretical and empirical results indicate that the approximate vector functions  $\mathbf{P}_i$  should be exponential vector functions of residence time, see for example Tessier et al. (2000). When the residence time is long, a steady-state model can be used. However, we experienced better results (both more accurate and less sensitive to sensor errors) with  $\mathbf{P}_i$  as second order polynomials for all stages. With the different states in stage  $i$  as  $Q_i$  and the different controls in stage  $i$  as  $C_i$  the polynomials used are

$$P_{ij}(\mathbf{z}_i, \mathbf{x}_i) = w_{ij}^0 + \sum_{q \in Q_i} (w_{ijq}^{z'} z_{iq} + w_{ijq}^{z''} z_{iq}^2) + \sum_{c \in C_i} (w_{ijc}^{x'} x_{ic} + w_{ijc}^{x''} x_{ic}^2) \quad (2)$$

We use the notation  $\mathbf{w}_i = \{w_{ij}^0, w_{ijq}^{z'}, w_{ijq}^{z''}, w_{ijc}^{x'}, w_{ijc}^{x''}\}$  as the vector of parameters for the polynomials for stage  $i$ .

### 3.3. Identification problem

In order to determine the approximations, the parameters  $\mathbf{w}_i$  in the approximate functions must be computed. A least-square optimization problem is formulated with the parameters as decision variables. We solve one problem  $[IP_i]$  for each stage  $i$ . In short, we set up the following vector function for stage  $i$ ,  $\mathbf{y}_i = \mathbf{F}_i(\mathbf{z}_i, \mathbf{x}_i, \mathbf{w}_i)$ , describing the relationships between output  $\mathbf{y}_i$ , initial state  $\mathbf{z}_i$ , control  $\mathbf{x}_i$  and parameters  $\mathbf{w}_i$ . The vector functions  $\mathbf{F}_i$  are defined through equation (2). The identification problem can be formulated as

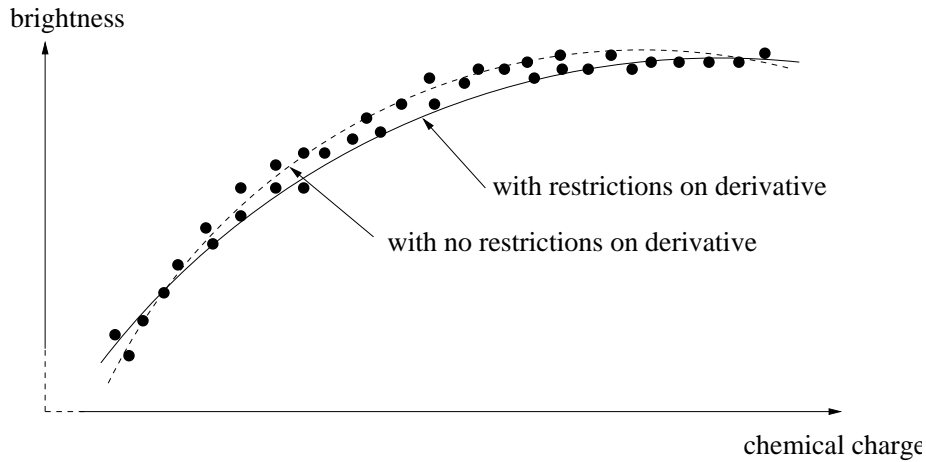
$[IP_i]$

$$\min \|\mathbf{F}_i(\hat{\mathbf{z}}_i, \hat{\mathbf{x}}_i, \mathbf{w}_i) - \hat{\mathbf{y}}_i\|_2^2 \quad (3)$$

$$s.t. \quad \mathbf{A}_i(\hat{\mathbf{z}}_i, \hat{\mathbf{x}}_i, \mathbf{w}_i) \leq \mathbf{b}_i \quad (4)$$

In the model,  $\hat{\mathbf{y}}_i$ ,  $\hat{\mathbf{z}}_i$ , and  $\hat{\mathbf{x}}_i$  are historical data. This model is solved with the parameters  $\mathbf{w}_i$  as variables. Constraint (4) represents practical restrictions, i.e. that the brightness will not decrease with increased chemical charge. This is illustrated in figure 6. Some constraints make sure that the approximation and variables are within certain bounds. Problem  $[IP_i]$  is a convex quadratic programming problem.

**Figure 6** Illustration of the condition on the derivative when finding an approximation relating the brightness obtained with the chemical charges for a set of measurement points. The dotted line would be the least square solution without the constraint and the solid line the least square solution with.



The process models, one for each bleaching stage, are determined dynamically, i.e., they are continuously updated due to varying production and pulp quality in each stage of the bleaching. Higher priority is given to more recent data. This is done by introducing a weight  $\eta_{ij}$  for each of the measurement points ( $j$ ) and stage ( $i$ ) in the objective function in equation (3). It is important that the plug flow model is accurate in order to relate correct input with the right time delayed output.

### 3.4. Control problem

Given the approximations from the identification problem, a control problem  $[CP]$  that integrates all the bleaching stages is formulated. In this model, we use the chemical charges ( $\mathbf{x}_i$ ) as control variables and some of the input and output properties ( $\mathbf{z}_i$  and  $\mathbf{y}_i$ ) as unknown state variables. The model can be formulated as



[CP]

$$\min \sum_{i=1}^n \mathbf{c}_i^T \mathbf{x}_i \quad (5)$$

$$s.t. \quad \mathbf{y}_i = \mathbf{F}_i(\mathbf{z}_i, \mathbf{x}_i, \hat{\mathbf{w}}_i), \quad i = 1, \dots, n \quad (6)$$

$$\mathbf{G}_i(\mathbf{z}_i) = \mathbf{y}_{i-1}, \quad i = 2, \dots, n \quad (7)$$

$$\mathbf{x}_i \geq \tilde{\mathbf{x}}_i, \quad i = 1, \dots, n \quad (8)$$

$$\underline{\mathbf{y}}_i \leq \mathbf{y}_i \leq \bar{\mathbf{y}}_i, \quad i = 1, \dots, n \quad (9)$$

$$\underline{\mathbf{x}}_i \leq \mathbf{x}_i \leq \bar{\mathbf{x}}_i, \quad i = 1, \dots, n \quad (10)$$

In the model,  $\mathbf{c}_i$  is the unit cost for chemicals in stage  $i$ .  $\underline{\mathbf{y}}_i, \bar{\mathbf{y}}_i, \underline{\mathbf{x}}_i$ , and  $\bar{\mathbf{x}}_i$  are lower and upper limit for the output and chemical charges, respectively, in stage  $i$ . The objective is to minimize the cost of chemicals. Constraint (6) represents the approximations. The function  $\mathbf{G}_i(\mathbf{z}_i)$  in Constraint (7) is used to link the output at the end of stage  $i-1$  with the correspondent state at the beginning of the next stage (for example to link the brightness after one step with the brightness of the beginning of the next step). A dynamic lower limit (parameter  $\tilde{\mathbf{x}}_i$ ) is used to prevent solutions with bang-bang characteristics. The dynamic lower limit allows the value of a control variable to only decrease by a small value between consecutive iterations. The functions describing the output in the different stages only give good approximations when the values of control and state variables are in the range of the historical data that was used to generate the parameters  $\mathbf{w}_i$ . Therefore, box constraints, i.e. lower and upper bounds on the variables, are used for all the output and control variables, see constraints (9) and (10), respectively. The control problem is a general non-linear problem.

The bound constraints on the output may be too limiting, and no feasible solution can be found. Since robustness is critical, we have modified the objective by adding penalized slack variables for such constraints. The same approach is also used for the dynamic lower limit constraints, giving the following problem

[CP2]

$$\min \sum_{i=1}^n (\mathbf{c}_i^T \mathbf{x}_i + M(\mathbf{s}_i^x + \mathbf{s}_i^{y-} + \mathbf{s}_i^{y+})) \quad (11)$$

$$s.t. \quad \mathbf{y}_i = \mathbf{F}_i(\mathbf{z}_i, \mathbf{x}_i, \hat{\mathbf{w}}_i), \quad i = 1, \dots, n \quad (12)$$

$$\mathbf{G}_i(\mathbf{z}_i) = \mathbf{y}_{i-1}, \quad i = 2, \dots, n \quad (13)$$

$$\mathbf{x}_i \geq \tilde{\mathbf{x}}_i - \mathbf{s}_i^x, \quad i = 1, \dots, n \quad (14)$$

$$\underline{\mathbf{y}}_i - \mathbf{s}_i^{y-} \leq \mathbf{y}_i \leq \bar{\mathbf{y}}_i + \mathbf{s}_i^{y+}, \quad i = 1, \dots, n \quad (15)$$

$$\underline{\mathbf{x}}_i \leq \mathbf{x}_i \leq \bar{\mathbf{x}}_i, \quad i = 1, \dots, n \quad (16)$$

Here  $M$  is a big number and  $\mathbf{s}_i^x, \mathbf{s}_i^{y-}$ , and  $\mathbf{s}_i^{y+}$  are the penalized slack variables for the dynamic lower limit on the control and the lower and upper limit on the output, respectively.

## 4. Implementation

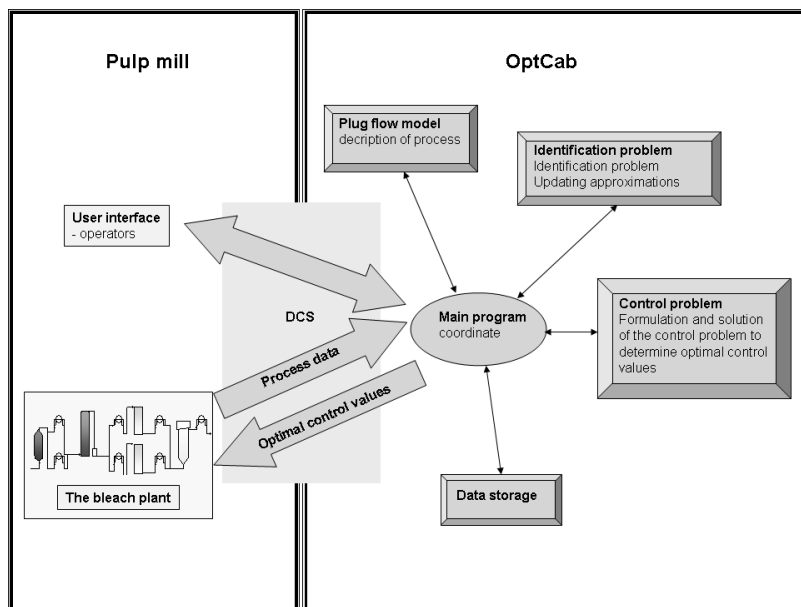
The current on-line process control system OPTCAB was developed in collaboration between Linköping University, Billerud AB's paper mill in Skärblacka and the software company Eurocon Automation AB. A first research prototype was developed in 2001. The prototype was based on a combination of user-built procedures to develop approximations and standard modules for modeling and optimization. It was only used to test data off-line. In 2002, disadvantages with the first prototype were identified and a further development of modules took place. The first, brief on-line test was held in May 2002. In 2003, the system - still a prototype with only small possibilities

for operators/process control staff to change parameter settings - was continuously tested and upgraded. From the end of 2003 and through the first half of 2004, the system was completely redesigned. At that point, the company Eurocon Automation AB took over maintenance responsibility and designed a user-interface while all of the optimization modules were redeveloped. The last version of OPTCAB was installed and put into operation at the end of 2004.

### OPTCAB system

The structure of the OPTCAB system is illustrated in figure 7. The main program is developed in a combination of Visual Basic and C routines. There are individual routines to handle the plug flow model, identification problem, control problem and data storage. There is a user-interface for the operators to change parameters such as limits and targets for brightness and limits to chemical charges. A distributed control system, (DCS), which is a part of the overall mill control system, is used to handle all data communication. A screen-shot from the user interface is given in figure 8.

**Figure 7** Overview of the main components in the OPTCAB system and its communication with the process system at the pulp mill.



### System data

In table 1, a complete description of the pulp properties (states) that are considered before and after the different stages, as well as the used chemicals (control), are given. We note that there are no properties given after tower D0 and the reason is that there is no measurement at this location. We tested to examine other pulp properties, for example residence time in tower EOP and tower D1A/B but this did not increase the quality of the approximations. We believe a steady-state situation is reached in these towers since the residence time is so long.

### Identification problem

Some data is faulty and is removed by means of incorrect sensor measurements. Some errors are easy to identify because the data, for example, is outside the sensor's operating area. Others can be removed by identifying data that is too far away from the approximations. This is done by solving

Figure 8 A screen-shot from the user interface where key values in the processes are shown.

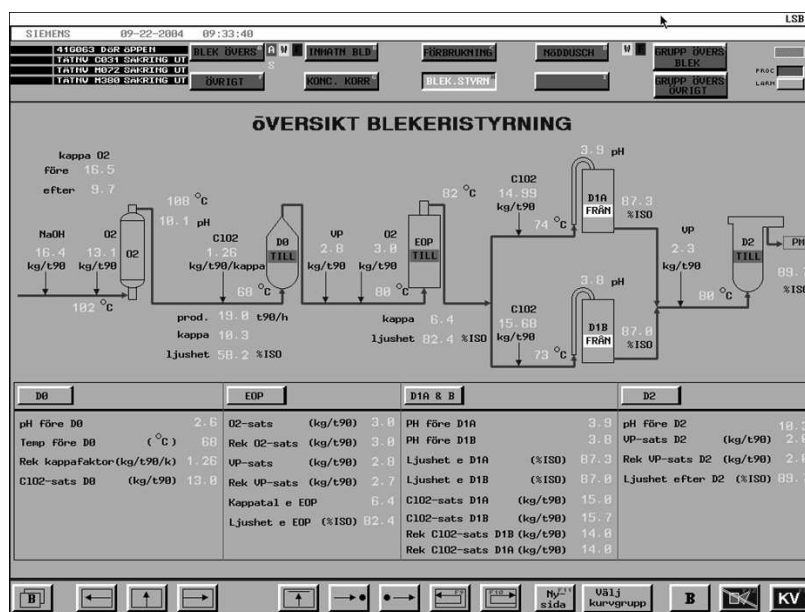


Table 1 Pulp properties (before and after towers) and control included in the system implemented at the paper mill in Skärblacka.

<u>tower D0</u>	<u>Pulp properties before</u>	<u>tower D1A/B</u>	<u>Pulp properties before</u>
	$\kappa$ (kappa number)		Brightness
	Brightness		$\kappa$ (kappa number)
	Temperature		Temperature
	pH (in)		pH
	residence time		
	pulp concentration		
	<u>Pulp properties after</u>		<u>Pulp properties after</u>
	Brightness		Brightness
	<u>control</u>		<u>control</u>
	chlorine dioxide		chlorine dioxide
<u>tower EOP</u>	<u>Pulp properties before</u>	<u>tower P</u>	<u>Pulp properties before</u>
	Temperature		Brightness
	pH		Temperature
	pulp concentration		pH
	residence time		residence time
	<u>Pulp properties after</u>		<u>Pulp properties after</u>
	$\kappa$ (kappa number)		Brightness
	Brightness		
	<u>control</u>		<u>control</u>
	hydrogen peroxide		hydrogen peroxide
	oxygen		

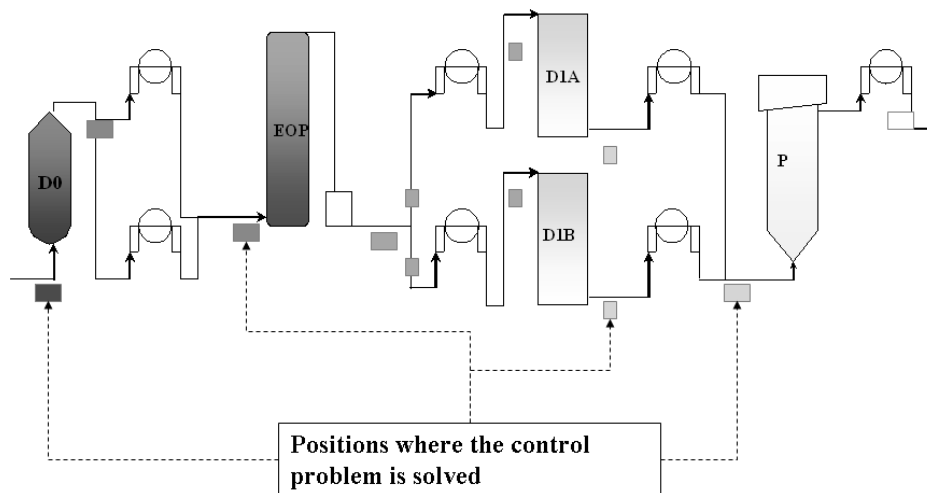
problems  $[IP_i]$  twice. Given the coefficients to the approximations from solving the problems  $[IP_i]$  the first time, the data that deviates more than a specific percentage ( $p_0$ ) from the approximations is removed and problem  $[IP_i]$  is solved again without the removed data generating new coefficients. This is tested in section 5.

The historical data is based on measurements over the previous week, with higher priority given to the most recent measurements. Typically we use 500 data points. Each identification problem has about 30 variables (parameter coefficients) and about 400 constraints and a typical update interval for the approximations is 15 minutes. Hardwood and softwood pulp respond significantly differently to a given control and input. Therefore, the historical data of the different types of pulp are separated and different parameters are generated.

### Control problem

When the pulp reaches the bleaching process, the control problem is solved, generating control values for the pulp throughout the bleach process (all stages). However, the approximated functions are not exact, and there may be changes in the process that were not known when the control problem was solved. For example, the production rate might change, the actual chemical charges may differ compared to the proposed optimal charges, the temperature in a tower may vary, etc. Therefore, when the pulp (pulp plug) reaches each of the other stages, the control problem is solved again, this time with fixed measured values for previous stages, and possibly more accurate data for the remainder of the process. Figure 9 illustrates where each  $[CP2]$  is solved. The further into the bleaching process the smaller the problem becomes. For pulp entering the bleaching process, problem  $[CP2]$  has typically 25 variables and 40 constraints, which is a relatively small problem. This is typically solved every five minutes.

**Figure 9** Positions where problem  $[CP2]$  is solved. The further into the process the more restricted (and smaller) the problem is.



Problem  $[CP2]$  is modified slightly. There is one quadratic penalty (instead of the linear) for the target brightness after tower P. It is in the form  $M * ([\hat{\mathbf{y}}_4^{target} - \mathbf{y}_4])^2$ . This is just to get a more smooth description of the deviation from the target. Both problems  $[IP_i]$  and  $[CP2]$  are solved with IPOPT, see Wächter and Biegler (2006). OPTCAB has been in operation for about four years with a practical usage level of more than 98%. The remaining proportion relates to planned maintenance and to operators' controlled overrides.

## 5. Results

In this section, we test different parts of the solution approach and report on experience from the use of the system during the last couple of years. First, we study the identification problem and how we can filter away potentially faulty data. Then we study the characteristics of the control problem and test four well known solvers. We then present the behaviour of cost and final brightness from long term tests. Finally we compare the stability of the final brightness between OPTCAB and manual solutions.

### Identification problem

Historical data is used to produce the approximations. In the basic version, information from about 500 plugs of pulp are used to determine the coefficients for the approximations. These comprise the most recent 150 plugs of pulp taken every 10 minutes and the remainder taken every hour. Data outliers are excluded, as described earlier, when the approximations are determined. If the measured output differs more than  $p_o\%$  from the approximation of the output, that plug of pulp is deemed as an outlier. A new approximation is then built without all outliers. More recent data is given more importance when creating the approximation by means it being given a higher weighting in the objective function for problem  $[IP_i]$ .

In the tables 2 and 3, we present results of the approximation accuracy when changes are made to the above data. The difference between the approximate value  $\mathbf{F}_i(\hat{\mathbf{z}}_i, \hat{\mathbf{x}}_i, \hat{\mathbf{w}}_i)$  and the measured value  $\hat{\mathbf{y}}_i$  is presented as the average of  $\epsilon^2 = \|\mathbf{F}_i(\hat{\mathbf{z}}_i, \hat{\mathbf{x}}_i, \hat{\mathbf{w}}_i) - \hat{\mathbf{y}}_i\|_2^2$ . The proportion of plugs that are deemed to be as outliers are presented in column "% outliers". One test is done when different requirements are given for data being treated as outliers (Outlier 0.5% up to Outlier 5.0%), see table 2. From the results, we get a best fit with the real data when only the plugs of pulp that differ more than 5.0% compared to the approximation are removed. In this test, the measurement quality was high. At the paper mill in Skärblacka, we remove all plugs of pulp that differ more than 2.0% compared to the approximation, to account for cases with more defect data.

**Table 2** Approximation quality with different requirement for outliers.

	Soft wood		Hard wood	
tower D1A	aver $\epsilon^2$	% outliers	aver $\epsilon^2$	% outliers
Outlier 0.5%	1.3667	61.54	1.5060	54.19
Outlier 1.0%	1.3265	36.49	1.5678	29.19
Outlier 2.0%	1.2393	10.23	1.3849	6.62
Outlier 5.0%	1.2160	0.20	1.0688	0.00
tower D1B				
Outlier 0.5%	0.8234	60.60	0.3870	39.07
Outlier 1.0%	0.8568	30.57	0.3868	12.96
Outlier 2.0%	0.8107	5.88	0.4083	1.66
Outlier 5.0%	0.7702	0.11	0.3739	0.19

In table 3, we compare the approximation quality when different data is used. One test is done when all 500 plugs of pulp are the most recent plugs, taken every ten minutes (Row "Every 10 minutes"), another test is when all 500 plugs of pulp are the most recent plugs taken one every hour (Row "Every hour"). A test when more recent data was not given more importance when the approximations are created is also given in the table (Row "Even importance"). These tests are only done for the approximations of the brightnesses after tower D1A and after tower D1B. The approximations of other output show similar behaviour. The base alternative which uses the most recent 150 plugs of pulp taken every ten minutes and the remainder plugs of pulp taken every hour

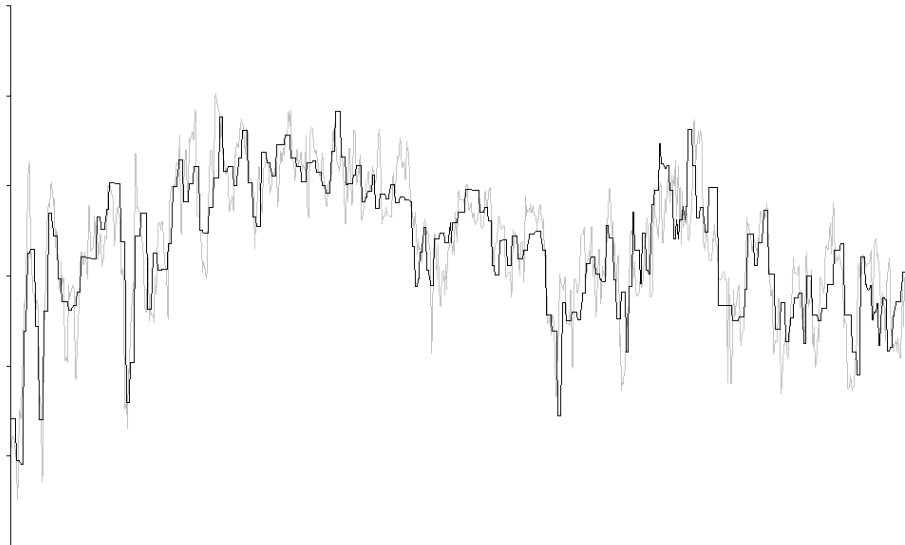
is similar to the other alternatives. In this case, the data quality is good. However, in cases when the measurement does not work properly for say two days, it is an advantage to include data for a longer time horizon in order to obtain good approximations.

**Table 3** Approximation quality using different data.

	Soft wood		Hard wood	
	tower D1A	aver $\epsilon^2$ % outliers	aver $\epsilon^2$ % outliers	
Base alternative	1.2393	10.23	1.3849	6.62
Every 10 min	1.2538	10.04	1.3948	6.91
Every hour	1.2646	7.99	1.3708	4.10
Even importance	1.3447	9.68	1.7359	6.35
<b>tower D1B</b>				
Base alternative	0.8107	5.88	0.4083	1.66
Every 10.0 min	0.8345	7.87	0.3464	1.78
Every hour	0.8116	4.44	0.3988	0.76
Even importance	0.7963	5.71	0.3562	1.37

Figure 10 provides an example describing the high quality of the approximations. It is an approximation of the brightness at tower D1B during a one week run. A high quality of approximation results in a reliable control.

**Figure 10** Comparison between real (black) and approximate brightness (grey) during a period of one week.



### Control problem

In table 4 results from solving Problem [CP2] for 4,500 consecutive plugs of pulp (entering the bleaching process) with different solvers are presented. The solvers tested are NPSOL (Gill et al. (1986)), IPOPT, DONLP2 (Spellucci (1998b) and Spellucci (1998a)) and MINOS (Murtagh and Saunders (1998)). Runs were done both with and without the dynamic lower limits, since the problem with dynamic lower limits is easier to solve. Objective values are compared for the different solvers standard settings. The number of runs a specific solver gives an objective value within a certain

percentage ( $p_g$ ) from the best found objective value which is presented in column  $\# \leq p_g\%$ . The number of times a solver produces an objective value that is more than  $p_b\%$  higher than best found objective value is given as  $\# \geq p_b\%$ . It is obvious that the problems are non-convex with many local optima. The best performance is given by the solvers IPOPT and NPSOL. For example, NPSOL provides the best solution (within 0.001%) in 3,934 cases out of 4,500.

**Table 4** Solving Problem [CP2] with different solvers with and without dynamic lower limits. The total number of runs is 4,500.

from best solution	<b>With</b> dynamic lower limits				<b>Without</b> dynamic lower limits			
	DONLP2	IPOPT	NPSOL	MINOS	DONLP2	IPOPT	NPSOL	MINOS
$\# \leq 0.001\%$	1457	3796	3934	406	1517	3651	3912	441
$\# \leq 0.01\%$	1541	3800	3940	414	1594	3655	3918	451
$\# \leq 0.1\%$	1685	3829	3974	448	1725	3693	3964	482
$\# \leq 1.0\%$	2072	3924	4055	536	2052	3780	4054	585
$\# \leq 2.0\%$	2304	3967	4095	606	2260	3813	4099	654
$\# \leq 5.0\%$	2828	4149	4263	729	2691	3977	4247	799
$\# \leq 10.0\%$	3193	4388	4438	891	3013	4188	4419	1006
$\# > 10.0\%$	1307	112	62	3609	1487	312	81	3494
$\# > 100\%$	26	7	11	2362	202	196	7	2148

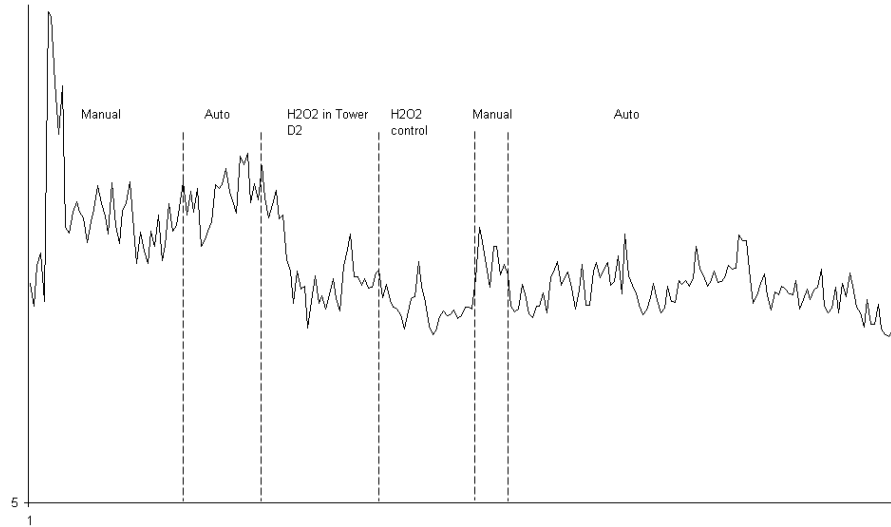
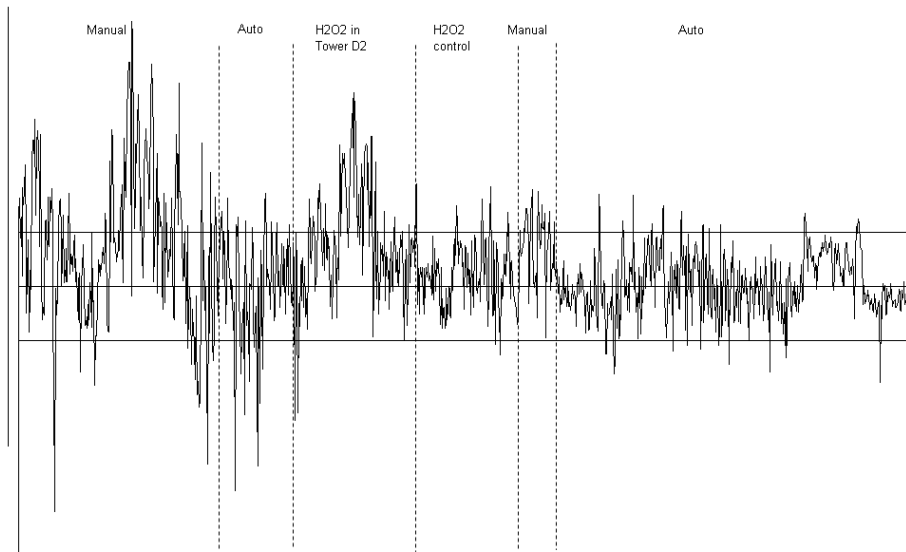
We made similar runs for the other more restricted control problems (by fixing the data from earlier stages) but since they are easier to solve, we only present results from the full version of [CP2]). The same solvers were used to solve  $[IP_i]$ . All solvers reached the same solution for each sub problem except for DONLP2 which failed in about 4% of the runs. We note that this problem is a convex quadratic programming problem i.e. each local optimal solution is the global optimum.

### System - performance

Figure 11 shows the cost of using bleaching chemicals to bleach soft wood during a period of 19 months. (The actual values are omitted because of confidentiality.) The presentation starts six months before OPTCAB was in operation to show the changes in the costs of chemicals over time. This first period is indicated as (Manual). Then follows a period (Auto) when OPTCAB was used. At one stage, there was a decision to use hydrogen peroxide instead of chlorine dioxide in the last stage (P). For some time, this tower was controlled entirely by the operators. Then there was period when OPTCAB was used again. For three weeks the system was turned off in order to compare the benefits with the system with manual control. Since then, the system has been in operation without interference. Figure 12 shows the final brightness (after tower P) for the same period.

### System - cost

When introducing a new system it is always difficult to measure the actual savings. This is because there are many other continuous developments in other parts of the overall process control system which influences the overall savings. In order to measure and analyze the direct impact, the system was turned off and the operators ran the manual system for a period of three weeks. OPTCAB was running in parallel (but in the background) during the manual period. This test result is given in figure 13. The chemical costs for the control suggested by OPTCAB were 10% lower than the cost reached when the process was controlled by the operators. Other measurements and experience have validated this number.

**Figure 11** Cost per metric ton over 19 months of operations.**Figure 12** Final brightness over 19 months of operations. The middle horizontal line is the target level and the other two horizontal lines the limits.

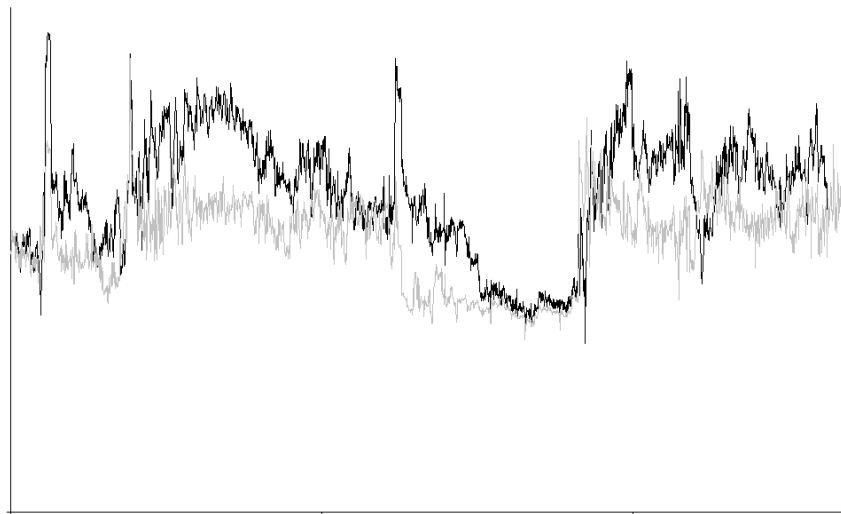
Instances in figure 13 with OPTCAB have a higher value than the manual system, relates to situations when the manual solution failed to meet the constraint on brightness. The main savings using OPTCAB compared to manual control are reached when the properties of the pulp change quickly. OPTCAB reacts instantly and makes necessary changes to the control while a manual controller often tests a few different levels of control before finding the right one.

### System - brightness

OPTCAB is designed to minimize chemical costs subject to a number of restrictions. There are additional positive effects. One is that the final brightness is more stable and follows the target value more precisely. When the system was turned off for three weeks we wanted to test two factors.

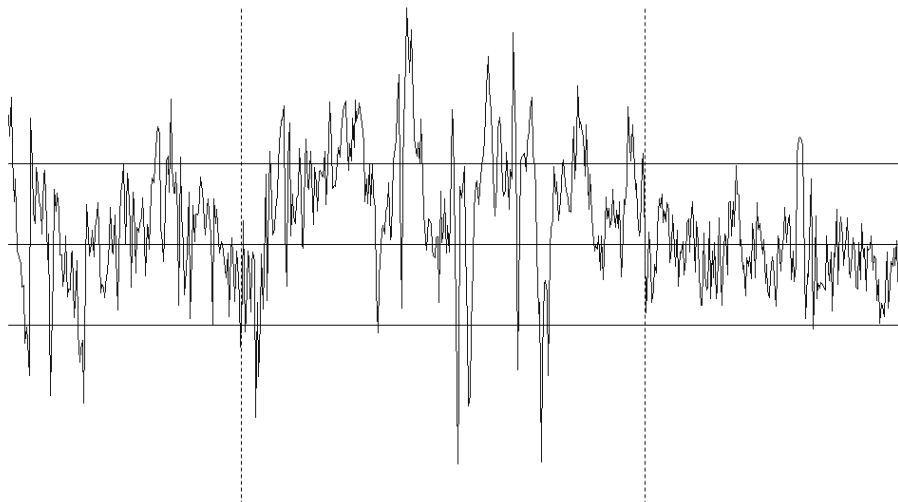


**Figure 13** Comparison of cost between manual operation (black line) and OPTCAB (grey line) during the three weeks when the system was turned off.



First, we wanted to study the average distance from the target level. Second we wanted to study the oscillating behaviour. In figure 14 we show the final brightness during the three weeks when OPTCAB was closed down and two weeks before and after as a comparison.

**Figure 14** Final brightness during three weeks (middle part) when OPTCAB was turned off and two weeks before and after.



We use a normalized brightness error measurement as the average squared deviation from the target value of the brightness to compare the brightness quality. The average normalized brightness error during the month before and the month after the three weeks of manual control was 0.13 and 0.50 for hard and soft wood, respectively. During the three weeks of manual control, the average normalized brightness error was 0.35 and 1.10, respectively. The error for soft wood could have been even lower if the brightness requirement after the stage in the towers D1A and D1B had been

lower. A low value of the average normalized brightness error is important for the paper quality in later stages.

The standard deviation of the brightness is also lower for the months before and after the manual run. Before and after it is 0.13 and 0.29 for hard and soft wood respectively and during the manual run it is 0.26 and 0.41 respectively. These two results shows that OPTCAB provides both a better brightness with regard to the target level and less oscillating behaviour.

## 6. Concluding remarks

We have presented a two phase solution approach for process control. The first is to use process data and establish accurate approximations describing the processes. The second is to formulate an overall control problem which is solved to give the amount of chemicals to charge continuously to the bleaching process. Within the process we also include the possibility to remove low quality or potentially faulty measurement data. This approach has been implemented and been running in on-line operations for the last three years. The solution process is general and can be used for other pulp and paper mills. The solution times are quick and enable on-line process control.

Introducing an automatic black-box system is difficult. In the manual system operators controlled the process, and there was a tendency to use a safety margin, for example, with regard to the final brightness. This margin, of course, is very individual. OPTCAB is an optimization-based system and will find solutions that are close to, or on, the bounds. In situations when the properties of the pulp change quickly, OPTCAB reacts instantly and makes changes in the control. In the beginning, when the system was new, some operators became cautious, turned off the system and used manual control. After some time, the operators became more confident with the system and let it work on-line without any interference. The system has been in practical use for four years and the operators have found it easy to use. Feedback from operators has been a critical element for understanding the process and being able to develop the user-interface.

There are several positive effects beside lowering the chemical costs. One is that the final brightness is more stable and follows the target value more precisely. The experience is that the volume of pulp within the brightness target limits increased by more than 50%. This is important for the paper quality in later stages. A second benefit is that the operators can now spend time on other issues such as preventive maintenance instead of continuously monitoring the process control. A third aspect is the improved environmental impact resulting from lower chemical usage.

Quality in data is critical for this type of automatic system. At the paper mill in Skärblacka we have been fortunate to have access to high-quality sensors for pulp brightness - the most important property measured. We have noticed that OPTCAB can be used off-line to identify faulty sensors. This is an interesting development that can be introduced in the on-line operations and give warnings to the operators.

## Acknowledgments

The authors acknowledge the contributions of the project team and operators at Billerud AB's paper mill in Skärblacka and the company Eurocon Automation AB for their work in the past year to develop OPTCAB into a full industrial system.

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