Improving the Efficiency of a Pulp Bleaching Plant through Data-Based Modeling

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Abstract

The kraft pulp bleaching process presents significant operational challenges due to its inherent non-linear reactions and unpredictable delays, complicating effective control and optimization. This thesis aims to improve the efficiency of the process through modeling it, and lays the groundwork for a new and improved automatic model-based control system. It explores a way of handling the varying delay by tracking the pulp throughout the process. This enables modeling of the chemical reactions using parameterized static models, fitted to existing production data. The models are used to create a decision support system to predict the future pulp quality from the bleaching process. The system showcases the possibilities of using model-based control to increase the efficiency of the plant. The pulp tracking also enables an evaluation of the current process, since it links input data to output data for the process.

Acknowledgements

I want start with thanking my supervisors at the university, Olle and Tore. They have helped me along the way with invaluable insights and guided me to the right path again when I felt lost. I also wanna thank my supervisor at Billerud, David, for giving me the tools and knowledge crucial to completing this thesis. I wanna extend my gratitude to Adam at Sigma, who helped with making this thesis happen, and has given me great coaching in how to make my work more valuable. Otto and Linus has been great friends throughout my studies, and I am forever grateful for them making my studies in Lund such an incredible experience!

Finally, I wanna thank my fantastic Lisa, who supports me every day.

Contents

1

Introduction

This is a master thesis conducted at the Karlsborg Mill in northern Sweden during the spring of 2024, as the last part of studies at the Faculty of Engineering at Lund University.

1.1 Purpose

Every day, we interact with various forms of paper, commonly white. The color is not by chance. The natural color of wood pulp, the primary material for paper, is brown, necessitating bleaching not only for printing reasons but also to improve structural integrity by removing particles. At the Karlsborg mill in northern Sweden alone, the production of bleached pulp reaches 335 kilotons annually [Billerud, 2024]. Given the scale, even minor reductions of the chemicals used in bleaching could significantly impact both economic and environmental aspects. This thesis explores the potential of improving bleaching efficiency through enhanced process control, specifically through modeling to predict pulp bleaching outcomes.

1.2 Aims of this study

- Investigate if the Karlsborg plant's bleaching process is suitable for modeling.
- Find models for the relationships between input and output variables for the bleaching process.
- Extend the models to handle varying rates of production.
- Improve the understanding of the bleaching process at the plant and find possible ways of improvement.

1.3 Earlier work

A challenge when attempting to model a pulp bleaching process is how to handle the bleaching plant's varying production rate, since it in turn brings a varying delay time for the process. Knowing the delay time is crucial to be able to model an input to an output later in time. Earlier implementations of model-based control strategies could be found to either use constant delays, based on a few set production rates, or to implement a tracking program for the flow of the pulp in the process. For the constant delay implementations, a common approach was to use first-order transfer function models with constant delay to describe the relations between the parameters in the system. Examples of this are [Mori et al., 2014], [de Oliveira, 2022]. For the other approach, where the delay modeling is done separately using a plug flow program, polynomial models were used. [Flisberg and Rönnqvist, 2007].

Methods to find the delay were also investigated, in [Mori et al., 2014], [de Oliveira, 2022], the first order models are found through system identification, where bump tests are performed on the bleaching process. A bump test means changing some input to the process in a controlled way, and then observing the resulting output. It can reveal different system characteristics, including the system delay. The drawback of bump tests is that they often affect the production quality negatively, making them expensive. Less invasive methods were also investigated. In another master thesis, [Dahlbäck, 2020], advanced methods like neural networks, but also simpler like cross correlation were tested. The conclusions were that it is difficult to employ advanced methods and that the results from these differ from the manual calculations for the delay that they did in the thesis.

1.4 Contributions and thesis structure

The master thesis begins by describing the pulp bleaching process, and configurations specific to the Karlsborg mill. This is presented in Chapter 2. Next up is investigating ways of modeling. With the earlier implementations in mind, the initial exploration used first-order with constant delay models. Since the production rate varied quite a lot, finding larger amounts of data from constant production proved difficult. Doing bump tests were also avoided, due to the high costs of running the production inefficiently.

The drawbacks of using a constant production rate led to the development of a pulp tracking program. The concept was inspired by [Flisberg and Rönnqvist, 2007], but with a new implementation, due to the limited amount of information about their program design. The pulp tracking program enabled creating datasets that linked input data to output data for the process. The program is described in Chapter 3. Based on the properties of the bleaching process, it was decided that the bleaching in a stage could be modeled as a static amplification. This enabled using parametrized polynomial models for the bleaching process, together with the input-output data-pairs that the pulp tracking program generated. The parametrized model structure is described in Chapter 4. The parametrized models, with coefficients trained on process data, were evaluated in Chapter 5. They could then be used in a decision support system, described in Chapter 6. The system was constructed with the purpose of guiding the process operators to which bleaching chemical dosages they should set for the process to achieve a desired bleaching result.

In addition to the decision support system, the constructed datasets of input-output pairs also brought new possibilities of evaluating the current control of the process. This was since, before the program, the input data could not be linked to the output data due to the varying delay. The evaluation is described in Chapter 7. The thesis also contains a discussion in Chapter 8, where the limitations of the implementation are discussed, and some reflections on future work. In the end, Chapter 9, there are some conclusions.

1.5 Scope

In order to constrain the workload of this thesis, the scope was limited to:

- The bleaching process contains two types of stages, chlorine dioxide based D-stages, and alkali based E-stages. The modeling focus was only on the D-stages, since they had better data and were deemed more important.
- Only existing data was used, no new data was created for this thesis.

2

The bleaching process

This chapter describes the Karlsborg mill's bleaching plant, the chemical reactions involved and the control of the process.

2.1 Introduction

Kraft pulp

Kraft pulp is created through a high-pressure cooking process. Small chips of wood are put into a tank and alkali is added. The pressure and temperature are then raised through the introduction of steam, which causes the lignin in the chips to dissolve from the fibers and create pulp. The cooking process creates chromophoric groups in the lignin, turning the pulp brown. Through the washing of the pulp, most of the lignin can be removed, but what is left needs to be bleached and further extracted to achieve a white pulp [Kassberg, 1996].

Process configuration

The specific configurations of pulp bleaching vary from plant to plant, as there are many ways to achieve the desired result. The general components, chemicals, sensors, and techniques are the same though. The difference from plant to plant is mainly in which order and quantity they are installed or used. In this chapter, the process is described as it is implemented at the Karlsborg plant. Details about the specific configuration are sourced from operators and plant schematics, referred to as [*Process knowledge* 2024], while components and concepts general to pulp bleaching are referred to with each individual source. A schematic of the process can be found in Figure 2.1, along with some terminology in Table 2.1.

Table 2.1 Bleaching stage definitions [Kassberg, 1996].

Symbol	Definition
D	Chlorine Dioxide (ClO_2) stage
EOP	Sodium Hydroxide (E), Oxygen (O), Hydrogen Peroxide (P) stage
E	Sodium Hydroxide (E) stage

Process overview

The bleaching process begins once the washed pulp exits the cooking stage. The first treatment is with pure oxygen, in a stage known as oxygen delignification, which reduces the lignin content in the pulp, the thesis does not address this part. Subsequently, the pulp enters the bleaching plant, where it undergoes a series of stages:

1. **D0 Stage:** The initial delignifying stage with Chlorine Dioxide (ClO_2), which oxidizes the lignin. The effectiveness of this stage is influenced by temperature, pH, and ClO_2 concentration. Stage duration around 1 hour.
2. **EOP Stage:** This stage uses Sodium Hydroxide, Oxygen, and Hydrogen Peroxide to further oxidize the lignin and dissolve the remnants from the D0 stage. Stage duration around 2 hours.
3. **D1 Stage:** Continues the bleaching process with another Chlorine Dioxide treatment. D1 and E2 stage duration together is around 3 hours.
4. **E2 Stage:** An Alkali Extraction stage that dissolves the chlorine dioxide-bleached lignin, preparing it for the final bleaching stage.
5. **D2 Stage:** The final Chlorine Dioxide treatment, completing the bleaching process. Stage duration around 3 hours.

This sequence is illustrated in Figure 2.1. After each stage, except for D1, the pulp is washed to remove any dissolved lignin and other chemicals [Kassberg, 1996]. The configuration of not washing the pulp after the D1 stage is unusual for this type of D-EOP-D-E-D bleaching sequence. [*Process knowledge* 2024]

Available measurements

In the bleaching plant, numerous sensors are installed and possible to gather data from. The ones most important to the modeling are presented in Table 2.2. Since the measurements are of a chemical medium, the measurements are prone to drifting. The drift requires regular maintenance in the form of calibrating and cleaning the sensor equipment. Several sensors have a specified error tolerance, and if the measured value is deviating enough from a lab sample, a calibration is performed [*Process knowledge* 2024].

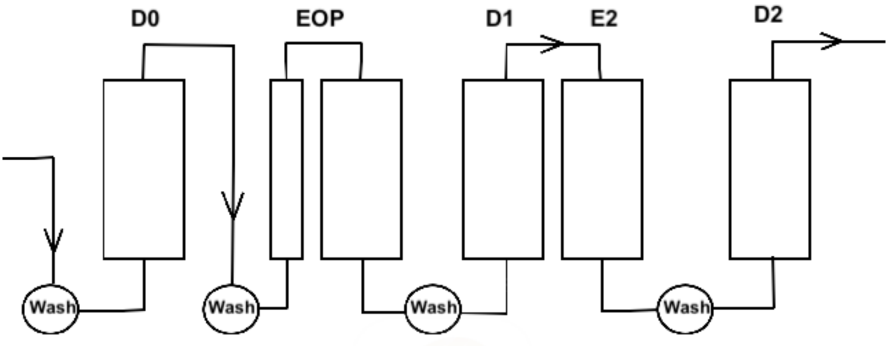


Figure 2.1 Karlsborg bleach plant process illustration. The illustration does not depict the oxygen delignification, which happens before the bleach plant [*Process knowledge* 2024].

Table 2.2 Table describing available measurements, details about kappa and brightness can be found in Section 2.2. The error tolerance is the largest allowed absolute value of the sensors measurement error, if the error is outside this tolerance, the sensor is calibrated. No relevant data indicated by – [*Process knowledge* 2024].

Type	Location	Sample Time	Error tolerance
Kappa	Before D0	20 min	0.7 Kappa units
pH	Before D0	Continuous	0.5 pH
Pulp Flow Rate	Before D0	Continuous	–
ClO2 Dosage	Before D0	Continuous	–
Brightness	After D0	Continuous	2 ISO Brightness
Fill height	In EOP	Continuous	–
Pulp Flow Rate	After EOP	Continuous	–
Kappa	After EOP	20 min	0.3 Kappa
pH	After EOP	Continuous	0.3 pH
ClO2 Dosage	Before D1	Continuous	–
Fill Height	In E2	Continuous	–
Pulp Flow Rate	After E2	Continuous	–
Brightness	After E2	Continuous	1 ISO Brightness
pH	After E2	Continuous	0.5 pH
ClO2 Dosage	Before D2	Continuous	–
Brightness	After D2	Continuous	1 ISO Brightness

2.2 Pulp quality measurements (kappa, brightness)

There are two main indicators of how bleached the pulp is: kappa and ISO-brightness.

Kappa

The kappa number corresponds to the amount of lignin left in the pulp. For kraft pulp, the fraction of percentage of dry pulp that consists of lignin and the kappa number is approximately 0.15. The definition of kappa number is the amount of potassium permanganate that can be absorbed by the pulp. The kappa number of untreated cooked pulp is around 30–35, and decreases along the bleaching process. For low kappa numbers, around 1–5, the method of determining the kappa is unreliable and brightness is used instead [Kassberg, 1996].

Brightness

Brightness, formally ISO-brightness, corresponds to the amount of light reflection at 457 nm. It is measured in percentage of reflection, and therefore increases as the pulp becomes whiter in the bleaching process [Kassberg, 1996].

2.3 Chemical reactions

The chemical reactions that achieve bleaching all have decreasing efficiency when the relative bleaching in each stage increases. This effect is reset when alkali extraction is performed, and this is why the bleaching is divided into separate steps. To achieve optimal efficiency, the amount of bleaching should be correctly divided among the steps. This effect is illustrated in Figure 2.2 [Kassberg, 1996].

Chlorine dioxide stages (D0, D1, D2)

The way that the chlorine dioxide stages work is different when comparing the delignifying stage and the bleaching stages. The delignifying stage, D0, operates at a pH of around 3. The chlorine dioxide reacts fast with pulp, the reaction is finished in around 10 minutes. The reaction has primarily a delignifying effect, with less focus on brightness increase. The majority of the lignin removed in the bleaching process is removed in this stage. The bleaching ClO2 stages, D1 & D2, operate at a higher pH, around pH 3.5 to 4.5. This means the ClO2 has a slower reaction with the pulp and primarily increases the brightness of it [Ragnar et al., 2014].

Alkali stages (EOP, E2)

In both the EOP and E2 stages, the alkali sodium hydroxide increases the solubility of the lignin. This process is necessary to enable further bleaching. The EOP stage also has the additional functionality of additional lignin removal with oxygen and hydrogen peroxide. This process is a complement to the D0 stage, where an

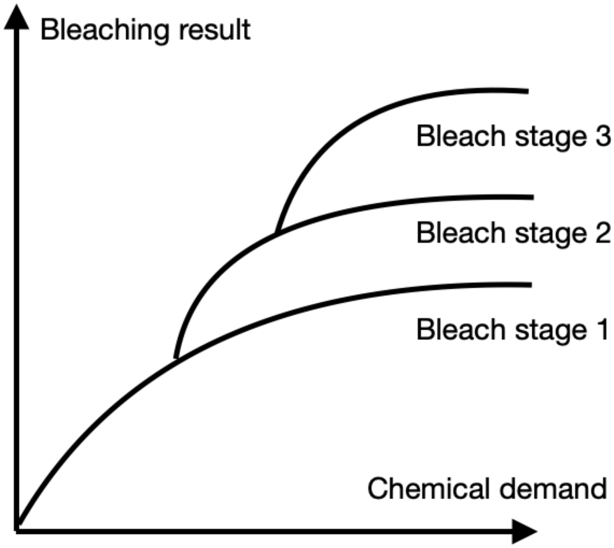


Figure 2.2 Brightness as a result of chemical demand. To achieve an increase in bleaching result, for example the increase in brightness in a stage, exponentially more chemicals need to be added. Dividing the bleaching among several stages can be seen to reset the curve, and enable a higher bleaching result. Figure recreated and translated from [Kassberg, 1996].

increased oxygen and hydrogen peroxide charge decreases the amount of chlorine dioxide needed in the D0 stage [Gellerstedt, 2009].

2.4 Process characteristics

Since the bleaching process is part of a continuous pulp flow, it heavily depends on the previous process stages. This is seen in the form of varying pulp kappa number of the incoming pulp, but also varying process production rate. The production rate can vary between 30 to 50 % some days, but also be constant for several days. The production rate is defined by the amount of pulp fiber mass that is passing through the stages. The available measurements are flow rate and pulp concentration, and from this, the mass can be calculated. The production rate mainly affects the time that the pulp spends in the bleaching stages, a higher rate meaning shorter delay times. The stages are designed to be large enough that the chemical reactions reach an approximately stationary state, independent of the process speed. The D-stages are also designed so that the pulp is inserted into the stage evenly to achieve a plug flow, meaning that no mixing occurs in the tank. The E-stages contain mixers in the lower part of the stage, where water is added to dilute the pulp. Water is also added at other places in the process, and filtered away in the wash filters. The mass ratio of dry pulp to water in the pulp is named pulp concentration. The E-stages operate at around 11 % concentration and the D-stages at around 12 % [*Process knowledge* 2024].

A study by Tessier et al. [Tessier et al., 2000] found that for a D0 tower operating at 3.2 % pulp concentration, 25 % mixing and 75 % plug flow was achieved. For a EOP tower operating at 12 % pulp concentration, 14 % mixing and 86 % plug flow was achieved.

2.5 Process control

The information in this part is sourced from interviews with process operation engineers and process operators, along with process schematics. Today, the bleach sequence is controlled by a combination of kappa factor control and manual control. The main actors for this control are the bleach process operators, which works in shifts and have the responsibility for changing dosages and making sure that the process runs correctly. There are also operations engineers, who support the operators by having a deep knowledge about the process and the pulp plant overall.

Control of each stage

D0. The kappa value of the D0 stage incoming pulp is measured, and this number is then multiplied by a kappa factor κ in the range 1.0 to 2.0. The product is the amount in kg of active chlorine being charged per ton pulp. Active chlorine is a measurement that represents the bleaching ability of a bleaching chemical, in this case chlorine dioxide. 1 kg of chlorine dioxide represents 2.63 kg of active chlorine. The factor is set manually, and is changed when the D0 output brightness is too low, or too high. It can also be changed because of information about process disturbances, for example incoming extraordinary high kappa numbers from the oxygen delignification, which need increased dosage. Information about malfunctioning or drifting sensors also affects decisions. For example, if the process operator know that a sensor for the concentration of a bleaching chemical is sending values that are too low, the dosage for that chemical is raised until the sensor has been recalibrated. The decisions to change dosages are taken by the process operators, sometimes with guidance from the operations engineers who they communicate with daily. Communication, for example about failing sensors, is aided through the usage of the factory production diary.

EOP. The sodium hydroxide charge for the EOP stage is set manually to achieve a pH of 10.5. Since the ClO2 charge in D0 affects the output pH, the sodium hydoxide charge has to be continually adjusted. The amount of oxygen and hydrogen peroxide that is charged per ton of pulp in EOP is set manually and rarely changed.

D1 & E2. The ClO2 charge in the D1 stage is based on kappa factor control in the same way as in D0. Here, the factor is more often adjusted by the operator compared to D0. The decisions are based on the state of the bleaching process, including the D1 and D2 output brightness, the EOP output kappa, and the amount of residual ClO2 after the D2 stage. The E2 stage following D1 has an automatic sodium hydroxide charge, with pH target slightly lower than in the EOP stage.

D2. The final D2 ClO2 stage does not have an automatic controller. Instead, the amount of ClO2 in kilos of active chlorine per ton of pulp is set manually. This amount is varied by considering output brightness of D1 and D2 and the amount of residual chlorine dioxide after D2. For example, if the output brightness is too low, the charge is raised, or if the residual chlorine dioxide is high, the charge is lowered.

Control challenges

From interviews with the operating staff, a few main challenges in controlling the bleach sequence can be identified:

1. The long delays in the stages make compensating for changes in pulp quality difficult. The way dosage changes are handled differs from operator to operator and also depends on communication between working shifts. Making too fast changes in dosage lead to an excessive impact on the process, wasting chemicals, while making too small a change also can lead to low pulp quality. Low quality can mean that it is not possible to sell the pulp.

2. The kappa number is slowly sampled, every 20 minutes, making fast changes in D0 incoming pulp kappa difficult to compensate for.

3. Sometimes, pulp of the same kappa number can require different amounts of bleaching chemicals to reach a lower kappa number, resulting in varying D0 kappa and brightness, with a need for correction in later stages. This is due to chemical properties of the pulp that are not represented by the amount of lignin in the pulp, and thus is not measured by the kappa meters.

2.6 Cost of bleaching

A study from 2007, [Flisberg and Rönnqvist, 2007], quotes the cost of bleaching to be around 30 euros per ton of pulp, which is 387 SEK per ton of pulp when adjusted for inflation and currency. With the Billerud Karlsborg yearly production of 335000 tons of pulp, then that equals 130M SEK per year in bleaching costs. The exact division of costs was not available, but an estimation is that half of the cost is in the E-stages and the other half is in the D-stages. If half the cost is in the D-stages, then the cost of bleaching for the D-stages is 75M SEK per year.

3

Gathering data through delay modeling

3.1 Background

To be able to create a model predicting the pulp bleaching results, two things were necessary: datasets with the crucial measurements, and a model able to represent the process. Since the delay in each stage varied with the plant's production rate, two options for estimating the delay were considered. These were to either use datasets captured during a constant production rate, and thus known delay, or develop a way of tracking the varying production. In related studies, both ways have been explored. In this work, initially the method of using datasets with constant production rate was tried. Since it was deemed time-consuming and difficult to find datasets with a constant production rate, it was decided to explore the other method, able to handle varying rates of production.

To handle varying production rates, a program tracking the pulp throughout the process was created. To track the pulp, the program required estimations of the volumes of the stages. With the program able to track the pulp, datasets linking input and output values for each stage could be created. The program and its components are described later on in this chapter.

3.2 Modeling for constant production rate

Modeling using System Identification Toolbox

Since there were several examples of using first order with delay transfer functions, [Mori et al., 2014; de Oliveira, 2022], this was tried first. It was done using the System Identification Toolbox in MATLAB [The MathWorks Inc., 2020b]. Since only a fixed delay could be used, datasets with a constant production rate had to be created. It was possible to fit models, but the problems of optimization and how to handle varying production rates became more and more evident. Through the assumption that the bleaching plant had longer delay times in the stages than what was needed for most of the chemical reactions to finish, it was decided that the bleaching process in each stage could be estimated as a static amplification. There probably could be minimal transient effects remaining, but they were deemed to be small enough. This led to the development of the pulp tracking program.

3.3 Pulp tracking program

Overview

The purpose of the pulp tracking program is to track how long the delay time is for each stage at each time. It also can create datasets that link input values to output values for each stage, as well as simulating control actions based on models of the process.

The pulp flow through the process is simulated in a discrete way, approximating the continuous pulp flow as discrete plugs of pulp. A new plug is created at each timestep and is then tracked throughout the bleach plant. The dataset creation and simulated bleaching control is done independently for each plug. The approximation of the pulp as a plug flow, meaning there is no mixing, is motivated by the results from [Tessier et al., 2000]. The study finds that pulp of the concentration used in the stages achieves almost plug flow. This is described further in Section 2.4.

Since the D-stages are tanks, which only can contain a finite volume, the inflow will be equal to the outflow. This means that the position of a plug of pulp in the tank can be computed if one knows the volume of the tank and the amount of pulp that has been added to the tank since the plug entered it. This is an approximation for the E-stages, since they are top-filled with a fill level that can vary, and thus have a varying volume. The position of a plug in a stage is indicated by its volume index, a higher index means that it has progressed further into the stage.

To calculate where each plug is in the process, the pulp flow-rate in each stage at each timestep is integrated. This results in a volume index increase, which is added to each plug in the stage. When a plug has a volume index equal or exceeding the volume of the stage, it must have exited. The plug is therefore removed from that stage and sent into the next one. When entering a new stage, the average of the process values during the timestep for the plug, such as brightness, pH, and dosage are saved to the plug. Since all the measurements and dosages happen before the pulp enters the stage, this approximation is reasonable. From the measurements, the optimal bleaching dosage can be calculated using a model of the process and the results of the calculation stored. This optimization possible in the plug tracking program was not used to a further extent in the thesis, the models of the process were instead used in the form of the decision support system in Chapter 6.

The sampling time for the plugs was chosen to be 5 minutes. This was chosen in respect to the available measurements, ranging from continuous to every 20 min-

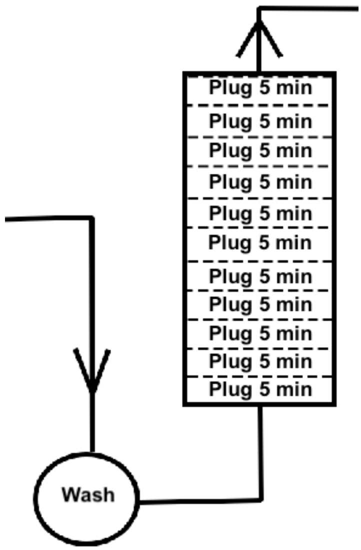


Figure 3.1 The flow of the pulp is approximated as discrete plugs. Each plug represents the pulp flow during 5 minutes. The volume index of the pulp at the bottom of the stage has zero volume index, while the plug at the top of the stage has a volume index close to the volume of the stage.

utes, the computations needed to run the program, and the accuracy of the stage volume estimations. The resulting pulp tracking for a stage is illustrated in Figure 3.1. Each five minutes, the input measurements are stored to a pulp plug. The plugs advance through the stage as more plugs are inserted, represented by increasing each plug's volume index. When the plug exits, the output measurements are stored to it.

Code design

The core of the program is encapsulated in two loops, one for stepping through time, and one for stepping through each plug object in a vector, representing the bleaching process. The program employs a `Pulp Plug` class with properties and methods that encapsulate the essential characteristics and behaviors of a pulp batch during the bleaching process. Attributes include the batch's ID, start time, current stage, and arrays to track chemical dosages and brightness levels. Methods allow for the updating of chemical dosages, brightness levels, and stage progression for the plug. The execution flow of the program for each timestep is this:

1. A new plug object is instantiated and added to the array of plugs. It is given an ID and start time, and has its volume index set to zero.

2. Through looping through the plug object array, each plug in the array has the current volume index increase for that plug's stage added to it. It is then compared to the stage's volume index threshold to determine the next action.

3. a) If the volume index is below the threshold, nothing happens. b) Otherwise, the plug is deemed to have exited the stage, and the stage's output values are saved to it. Then, if the plug was in the last stage, it is recorded and removed from the array. If it is entering a new stage, the new stage's input values are saved to it, and an optimal control solution for the bleaching chemical dosage is calculated and also saved to the plug object. The volume index of the plug is reset when entering the new stage.

A figure illustrating this process is provided below in Figure 3.2. The datasets that the program generate thus consists of the plug objects that are recorded when removed from the plug object array. The optimal control solution when entering a new stage uses a parametrized model of the process, created in Chapter 4. The control solution in the way that the program was used in this study was only for demonstration purposes and not used to any further extent.

Estimation of the pulp volume in each stage

Since the pulp tracking program required the pulp volume that each stage contains, these had to be gathered. The physical size of some stages were known from process schematics, but since the concentration of pulp changes throughout the process, it could not be used straightforwardly. The concentrations change, for example, when the pulp is washed between the stages, or diluted in the E-stages. This means that integrating the measured pulp flow out of a stage might not correspond to the actual volume of the pulp in the stage if the pulp is diluted between the stage and the flow sensor. If the dilution is constant, the flow sensor still can be used, but the additional volume of the dilution water has to be accounted for when integrating the flow measured by the sensor. To get an estimation of the pulp volume the stages contain, a manual correlation method was instead used. The method was to identify peaks and valleys in the incoming and outgoing kappa or brightness data for each stage. An estimate of the pulp volume each stage contains could thus be created by integrating the pulp flow during the time between the peaks. The estimation was then repeated and collected into datasets for each stage.

An example of how one data point is created is illustrated in Figure 3.3. A peak in the incoming brightness into the EOP stage can be seen, and a similar drop in the kappa of the outgoing pulp. Since a high brightness value corresponds to a low kappa value, these peaks can be determined visually. The exact time for the peaks were chosen to be in the middle of each peak, this was done manually. The time that has elapsed between the peaks is recorded, and also the mean pulp flow rate and the

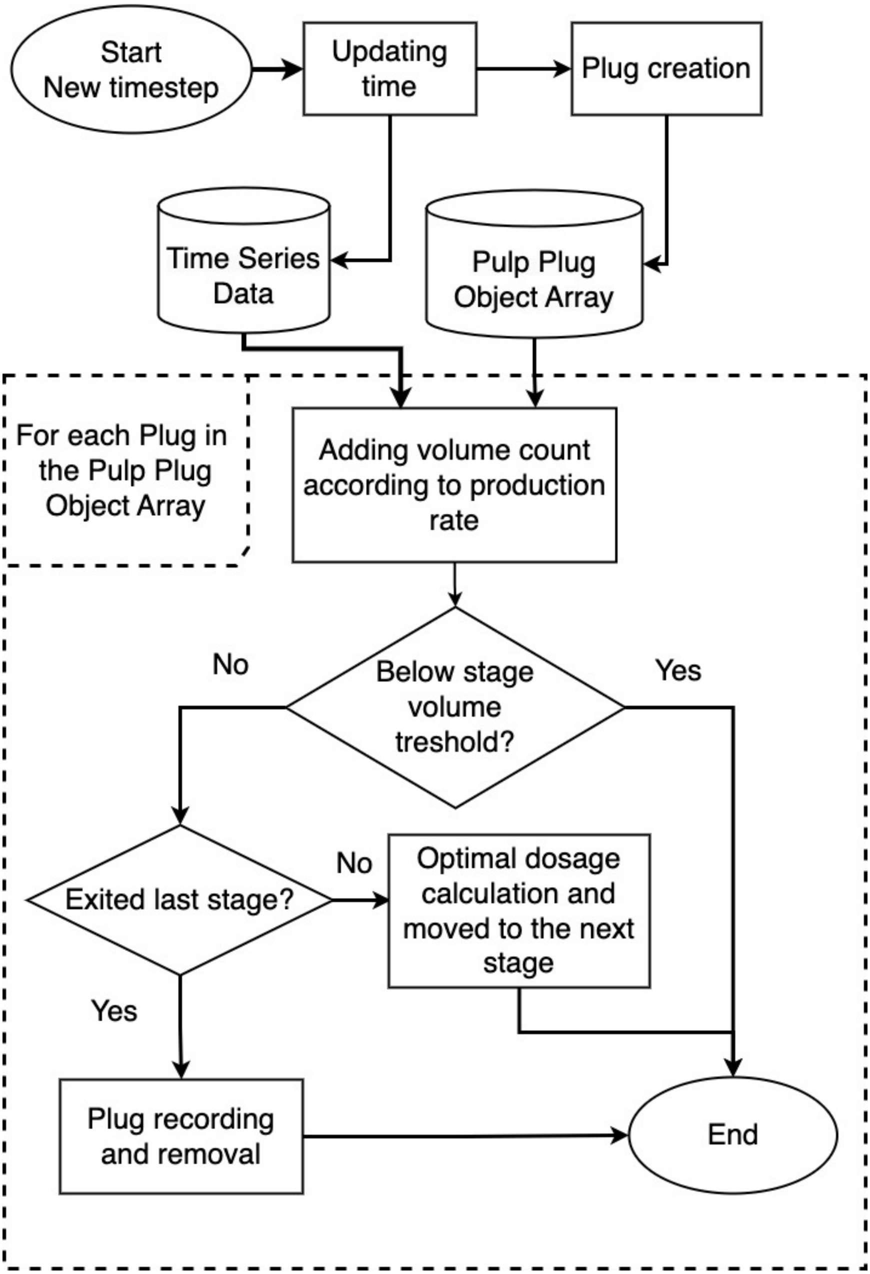


Figure 3.2 Schematic of one timestep iteration for the pulp tracking program described in Section 3.3

pulp fill height in the EOP tower. The method of choosing the peaks manually can be expected to be imperfect in matching the peak, and therefore needs to be repeated several times.

The collected datasets are presented in Figures 3.4 to 3.7. Since the E-stages fill height was thought to be affecting the retention time, this height is included for the EOP and D1-E2 plots. What can be seen is that the data for these stages has a quite high variance compared to the D0 and D2 data. Because of the higher variance, more datapoints were also collected for the EOP and D1-E2 datasets. The variance also does not seem to be explained by the height of the pulp. For the EOP stage, a slight slope can be noticed. This was, however, ignored and only the flow rate was hence used to calculate retention time for the stage.

Greater uncertainty for the volume estimation is expected from higher variance in the data. Due to the higher variance for the EOP and D1-E2 estimation, we expect that the volume may not be fully correct at all times. This means that some input-output pairs may be linked incorrectly, and this likely results in increased noise for the produced datasets for these stages by the pulp tracking program.

To verify the physical plausibility of the stage volume estimations, process schematics were consulted. Since the pulp concentration varies throughout the process, some estimations had to be made, and the results were that the estimated volumes were plausible, not differing more than 10 % from the process schematic calculations.

Dataset creation

The pulp tracking program enables using production data with varying production rates, since it connects the input to a stage with the correct output at a later time. Datasets with input and output production data that has been paired by the program can then be created. Suitable time-periods for dataset creation were chosen where the plant's pulp production did not have stops longer than a few hours. Long stops were avoided because they induce disturbances in pulp quality, which does not represent normal production. The factory production diary was also checked to find any information about abnormal production, problems with sensors or other factors affecting the production. Time-periods with problems deemed too problematic were discarded. Several datasets were created, the main analysis is presented for the dataset `Combined 23`. It includes data from March and December 2023 together with data from January 2024. A testing dataset was also created, named `March 2024`, taking data from a few days in March 2024. The Combined 23 dataset contains data from in total 73 days of production. The `March 2024` dataset contains 9 days.

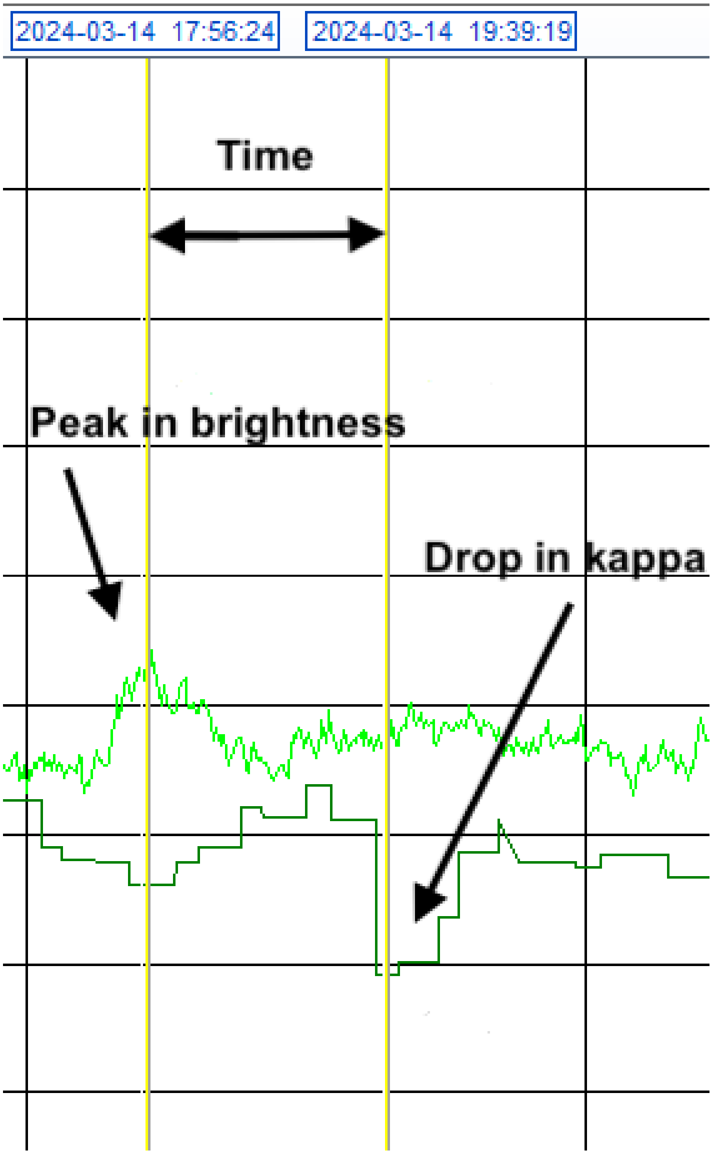


Figure 3.3 The manual correlation method used to estimate volumes. The figure is an example from the EOP stage, an incoming peak in the brightness will correspond to a drop in outgoing kappa. These peaks are identified, the time between them are measured, along with the flow rate and stage fill height. The flow rate is integrated during the measured time to create a volume estimation for the stage

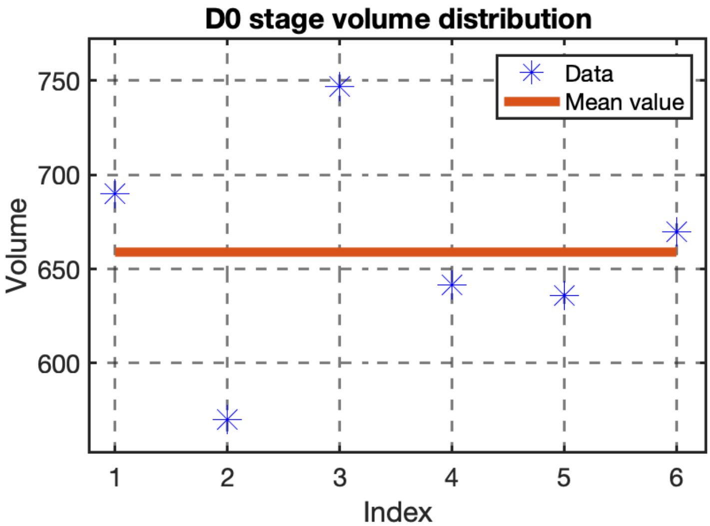


Figure 3.4 Plot of volume estimation dataset datapoints for the D0 stage, with a line representing their mean. Each datapoint is a result of one volume estimation as described in Section 3.3. The index represents the number of datapoints.

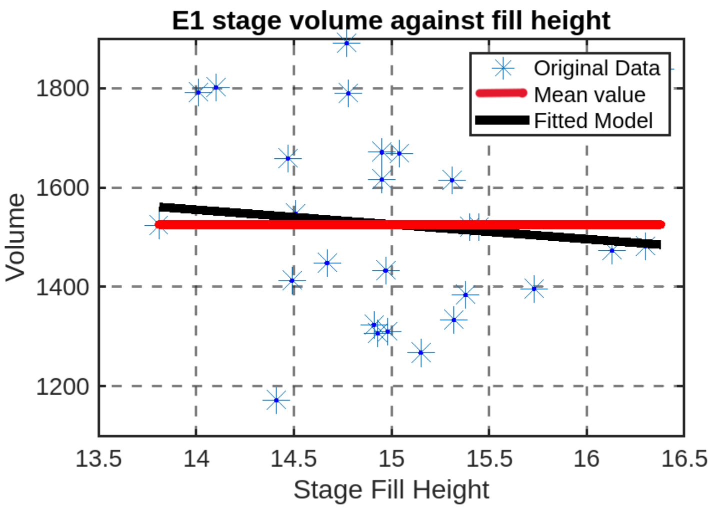


Figure 3.5 Plot of volume estimation dataset datapoints for the EOP stage, with a flat line representing their mean, and a sloped line displaying a first order model with stage fill height as a parameter. Each datapoint is a result of one volume estimation as described in Section 3.3.

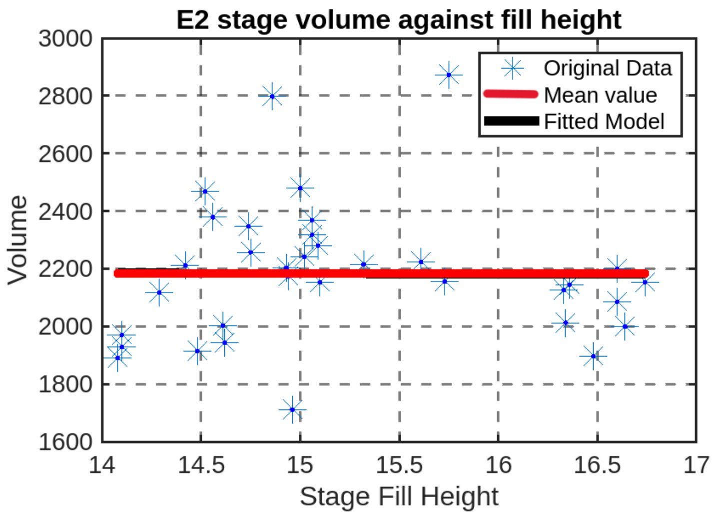


Figure 3.6 Plot of volume estimation dataset datapoints for the total volume of the D1 and E2 stages, with a line representing their mean. A first model order model with stage fill height as a parameter is also plotted, but not visible since it is equal to the mean. Each datapoint is a result of one volume estimation as described in Section 3.3.

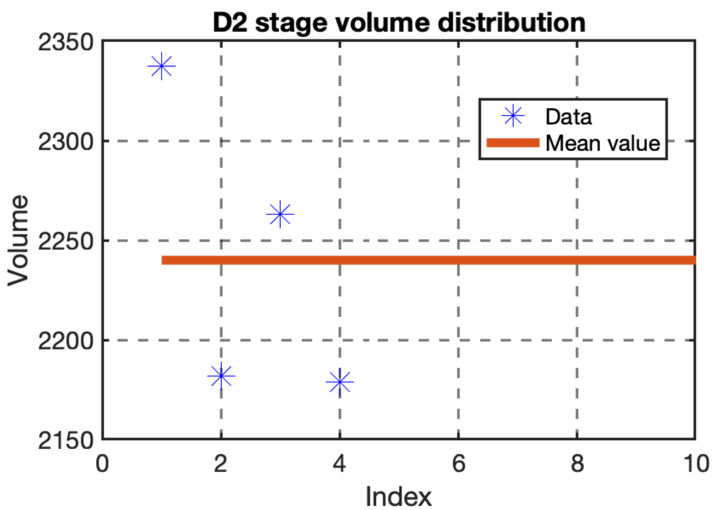


Figure 3.7 Plot of volume estimation dataset datapoints for the D0 stage, with a line representing their mean. The index represents the number of datapoints. Each datapoint is a result of one volume estimation as described in Section 3.3.

4

Structure of the parametrized model and tools for evaluation

This chapter describes the structure of a parametrized model designed to capture the workings of the bleaching process in each stage. It also describes tools for model evaluation.

4.1 Polynomial model

To capture the properties of the process, polynomial regression was employed. The focus was on polynomial models up to second order, incorporating interaction terms to better account for the interplay between variables. The reason for choosing the second order structure was the expected non-linear shape of the bleaching process, see Figure 2.2. The model is also static, meaning it does not take the process dynamics into account. That was because the delay time in the stages was deemed long enough for the process transient effect to become small.

The general form of the second order parametrized model is expressed as:

$$\text{bleachResultModel}(x,y) = p_{00} + p_{10}x + p_{01}y + p_{20}x^2 + p_{11}xy + p_{02}y^2. \quad (4.1)$$

Here, x and y represent factors influencing the bleaching result, whose interactions and quadratic effects are captured through the coefficients $p_{10}, p_{01}, p_{20}, p_{11}$, and p_{02}. Models with three input variables were also used, the model then extends with a third variable z and its corresponding interactions. The model is structured to provide an understanding of how these variables collectively impact the outcome, increasing the explainability of it.

4.2 What the models represent

Inputs used

For the models, three inputs were mainly used. These were the bleach chemical dosage, represented by either the kappa factor or the absolute dosage, the incoming pulp pH and the incoming quality, represented by either incoming pulp kappa or brightness. The reason for using these three inputs was that they are the most important when predicting the brightness.

Input to output relation

The parametrized models, structured as Equation (4.1), represent the cumulative effect of the input variables on the output. In this case, the combined effect of the input variables; bleaching chemical dosage together with pH and kappa of the incoming pulp, on the output variable, the brightness out. The relation is thus modeled for each D stage, and in total there are three different sets of values for the coefficients, one for each D-stage.

4.3 Finding parameter values

System identification

System identification through black box modeling means taking a pre-defined model and fitting its parameters to a dataset. A simple example is fitting a line for some data points. If we have an equation $y = kx + m$, then we want to get the values for the parameters k and m from the data points. This can be done for more complex models and in the time domain [Ljung et al., 2021].

The modeling in this study has mostly been performed with linear regression using second degree polynomials, and formally it works like this:

Given inputs at a time t denoted as $u_i(t)$ for $i = 1, 2, \ldots, m$, and an output as $y(t)$, we aim to model the relationship between $y(t)$ and the inputs $u_i(t)$ using a second-degree multivariate polynomial regression approach. The models used three inputs most of time, meaning $m = 3$. This method is capable of capturing both the individual effects of each input and their interactions on the output.

The discrete time model, assuming no noise for simplicity, can be stated as

$$y(t) = f(\mathbf{u}(t), \theta) \tag{4.2}$$

where f is a second-degree polynomial function of the inputs $\mathbf{u}(t) = [u_1(t), u_2(t), \ldots, u_m(t)]$ with coefficients represented by the parameter vector θ.

For a second-degree multivariate polynomial regression with interactions, the model can be explicitly written as

$$y(t) = \theta_0 + \sum_{i=1}^{m} \theta_i u_i(t) + \sum_{i=1}^{m} \sum_{j=i}^{m} \theta_{ij} u_i(t) u_j(t) \tag{4.3}$$

To optimize the parameter vector θ, we construct a matrix X to include the linear terms, interaction terms, and quadratic terms of the inputs. This involves creating additional columns in X for every pairwise interaction and every squared term, leading to

$$X(t) = \begin{bmatrix} 1 \; u_1(t) \; \cdots \; u_m(t) \; u_1(t)u_1(t) \; \cdots \; u_1(t)u_m(t) \cdots \; u_m(t)u_2(t) \cdots \; u_m(t)u_m(t) \end{bmatrix}. \tag{4.4}$$

The coefficients in $\theta = [\theta_0, \theta_1, \ldots, \theta_i, \theta_{1j} \ldots, \theta_{ij}]^\mathsf{T}$ are estimated by minimizing the squared error between the observed outputs $y(t)$ and the model's predictions.

The optimization objective, in this case, is defined as

$$\hat{\theta} = \mathrm{argmin}_\theta \sum_{t=1}^{N} (y(t) - X(t)\theta)^2. \tag{4.5}$$

Here, $X(t)$ represents the t^{th} row of the design matrix X, which now includes the terms necessary for capturing both the individual and interactive effects of the inputs on the output.

Optimization. The optimization of the parameter vector θ was performed using MATLAB [The MathWorks Inc., 2020b]. The `fitlm` function in MATLAB takes the matrix X and the target vector $y(t)$ as inputs. It outputs the estimated parameter vector $\hat{\theta}$, along with the fit RMSE and r-value. The `fitlm` was used with standard configuration, meaning it uses QR-decomposition to solve the least squares optimization objective [The MathWorks Inc., 2020a].

Predictions and error measure

With the estimated coefficients $\hat{\theta}$, the output $\hat{y}(t)$ for any given set of inputs $u_i(t)$ is predicted by

$$\hat{y}(t) = \hat{\theta}_0 + \sum_{i=1}^{m} \hat{\theta}_i u_i(t) + \sum_{i=1}^{m} \sum_{j=i}^{m} \hat{\theta}_{ij} u_i(t) u_j(t) + \sum_{i=1}^{m} \hat{\theta}_{ii} u_i^2(t). \tag{4.6}$$

The difference or error $\varepsilon(t)$ between the estimated output $\hat{y}(t)$ and the actual measured output $y(t)$ is given by

$$\varepsilon(t) = y(t) - \hat{y}(t). \tag{4.7}$$

A measure of this error is the Root Mean Square Error (RMSE). It is a standard way to measure the error of a model in predicting data. It represents the square root of the average squared differences between the predicted values and the actual values, Equation 4.8. In essence, RMSE quantifies how much, on average, the model's predictions deviate from the observed values. A lower RMSE indicates a better fit of the model to the data.

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{4.8}$$

4.4 K-fold cross validation

K-fold validation is a model validation technique that works by dividing the available data into K subsets (or folds). In each iteration, one fold is retained as the test set and the remaining K-1 folds are used as the training set. The model is trained on the training set and validated on the test set, and the process is repeated K times, with each fold used exactly once as the test set. In this study, the mean RMSE of the test folds has been used as an accuracy measure. This method provides an evaluation of a model on unseen data, while making use of all available data for training and validation across the iterations [Jung, 2022]. In the thesis, five folds of equal size were used. The folds were created using continuous data, not split up internally in any way.

5

Evaluating and fitting the parametrized models

In this chapter, the parametrized models from Chapter 4 are fitted to data and their predictive capabilities are evaluated.

5.1 Model evaluation

The parameterized model structure were evaluated through creating models with parameters fitted to data. Two kinds of evaluations were performed; the M1 model with training on the `Combined 23` dataset with predictions on the `March 2024` dataset. The other, the M2 model, with k-fold validation on only the `March 2024` dataset. Both models thus predicts on unseen data, and it is the RMSE of the predictions that are discussed. Some other combinations were also experimented with, for example using only parts of the `Combined 23` dataset. What can be seen in Figures 5.1 to 5.6, and Table 5.1, is that the M2 model performs better in terms of RMSE. The difference in RMSE between the two methods can be seen to be different for each stage.

It can also be seen that the RMSE is the lowest for the D2 stage. What has to be noted, though, is that the brightness has a lower variance compared to the D0 and D1 stages. It is thus easier to achieve a low RMSE on D2 compared to the D0 and D1 stages. When observing the plots, especially for the D0-data, some large peaks and drops in brightness can be seen that the model does not predict. This is investigated in the residual analysis later on.

In the plots, for example in Figure 5.3, one can also note that the accuracy is good initially and then worse later on. This could be due to sensors being recalibrated, or that the properties of the pulp change. Since the pulp is created from large batches of wood, some properties, especially how easy the pulp is bleached, can change. When experimenting with the fitted models, the effect of training the model on a small amount of data, and then predicting on new data further into the future, was tried. The result was that the predictions had large errors. The models

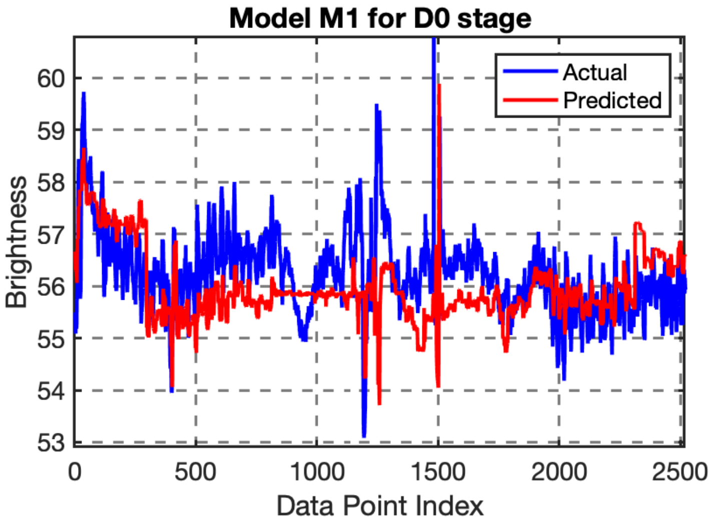


Figure 5.1 Predictions for D0 pulp brightness out by M1, the model trained on Combined 23 dataset, tested on March 2024. Average prediction error RMSE of 0.9095. The large peak in actual values goes up to 65.2 ISO brightness. Each data-point represent 5 minutes, meaning that 1000 points is around 4 days.

fitted on the small dataset were also tested with bleaching chemical dosages different from what they had been fitted on. The results were that the predictions were unreasonable, with large errors.

Table 5.1 Prediction residual RMSE results for M1: the model trained on Combined 23 dataset, tested on March 2024, and M2: the model using K-fold validation on March 2024.

Stage	RMSE for M1	RMSE for M2
D0	0.91	0.52
D1	0.72	0.42
D2	0.31	0.13

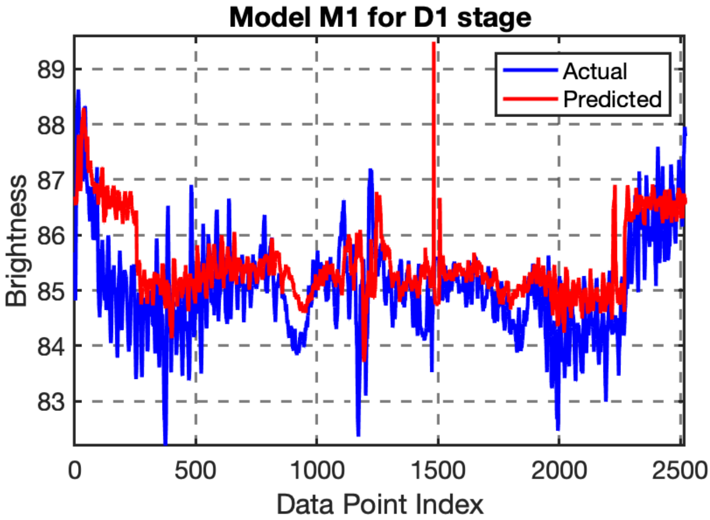


Figure 5.2 Predictions on D1 pulp brightness out by M1, the model trained on Combined 23 dataset, tested on March 2024. Average prediction error RMSE of 0.7191. Each datapoint represent 5 minutes, meaning that 1000 points is around 4 days.

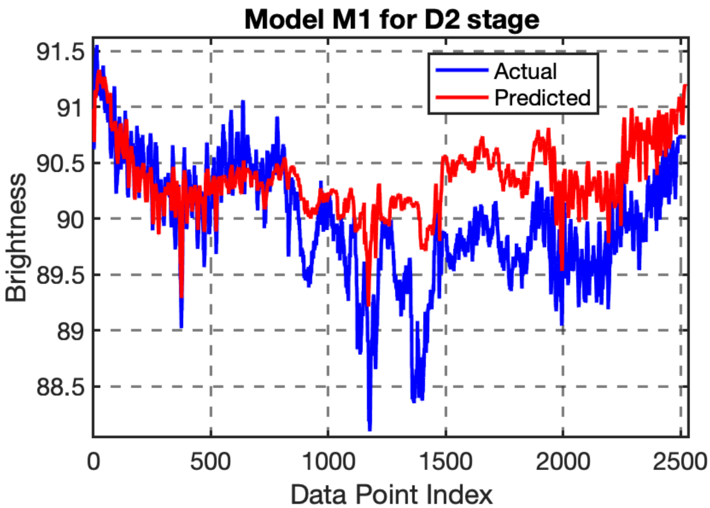


Figure 5.3 Predictions on D2 pulp brightness out by M1, the model trained on Combined 23 dataset, tested on March 2024. Average prediction error RMSE of 0.3060. Each datapoint represent 5 minutes, meaning that 1000 points is around 4 days.

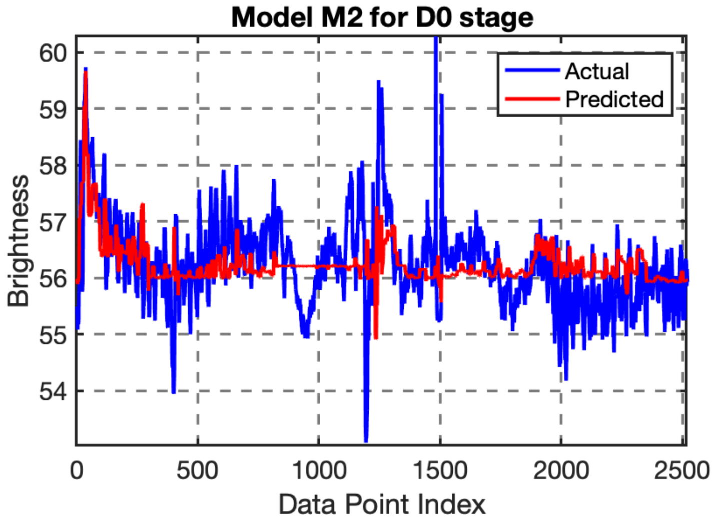


Figure 5.4 Predictions on D0 pulp brightness out by M2, the model trained and tested on March 2024 dataset. Average prediction error RMSE of 0.5217. Each datapoint represent 5 minutes, meaning that 1000 points is around 4 days.

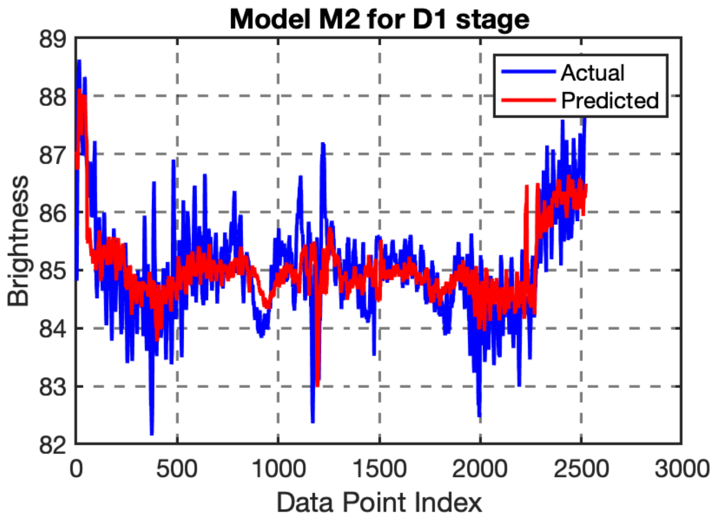


Figure 5.5 Predictions on D1 pulp brightness out by M2, the model trained and tested on March 2024 dataset. Average prediction error RMSE of 0.4244. Each datapoint represent 5 minutes, meaning that 1000 points is around 4 days.

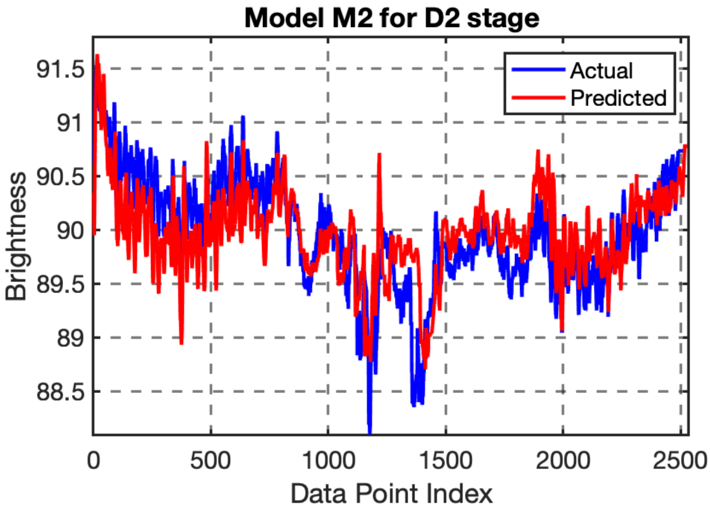


Figure 5.6 Predictions on D2 pulp brightness out by M2, the model trained and tested on March 2024 dataset. Average prediction error RMSE of 0.1280. Each datapoint represent 5 minutes, meaning that 1000 points is around 4 days.

Residual analysis for D0

Since the predictions for the D0 stage contained several peaks and drops that the predictions missed, a more detailed residual analysis is presented for the largest positive and negative residual. A prediction residual is defined as the difference between the predicted series and the real series. The residuals are extracted using the model using the full second order structure, the same used in the previous evaluation. It was trained on the March 2024 dataset, and also predicted on the March 2024 dataset. The prediction residuals were produced without k-fold validation.

The largest positive and negative residual are indicated by vertical lines in Figure 5.7. To analyze what they could have been caused by, all the incoming data are also presented, with the same indices marked in the plots. To begin with, when observing Figure 5.8, it can be noted that the brightness output correlates a lot with the residuals. When observing the two indices 1297 and 1482 in the input variables, Figures 5.9, 5.10,5.11, it can be noticed that no peaks or drops appear there. For the first index at 1297, corresponding to the large negative residual, it can be noticed that both the kappa in and dosage increase rapidly shortly thereafter. For the second index at 1482, a slight drop in incoming kappa can be seen. This could partly explain the large increase in brightness, but the measured brightness can be seen to be much larger than the rest of the series, and the measured kappa seems normal. The large peak in brightness therefore could be a result of a misreading in the sensor, but it is also possible that the slow sample time of the kappa sensor missed a very low kappa number in the pulp.

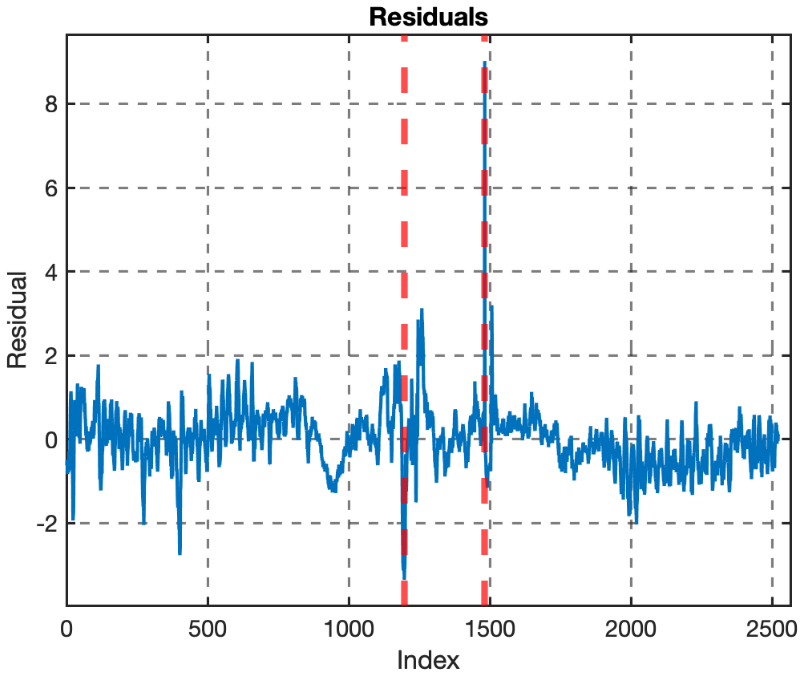


Figure 5.7 The residuals when predicting the brightness output out of D0, using the M2 model. The model was trained and predicted on March 2024. A drop at index 1297, and a peak at index 1482 have been indicated with the vertical lines.

The kappa sensor can be seen to be malfunctioning for a period around index 1000, the measurement it is recording is constant. This malfunction was not indicated in the factory production diary, and was thus included into the dataset. What this means for the prediction during that period is that the kappa variable does not provide any information about the brightness result, and thus stays constant. The only inputs making the predictions to vary are thus pH and dosage, and since they can be seen to vary quite slowly, the predictions does not change much. The prediction residual can therefore be seen to be almost identical to the real brightness out since the predictions are almost constant.

A conclusion that can be drawn is that the kappa measurement is vital for the models predictions to be accurate. When the model predicts the worst, the kappa measurement can be seen to not be correct. A accurate kappa measurement therefore should lead to more accurate predictions.

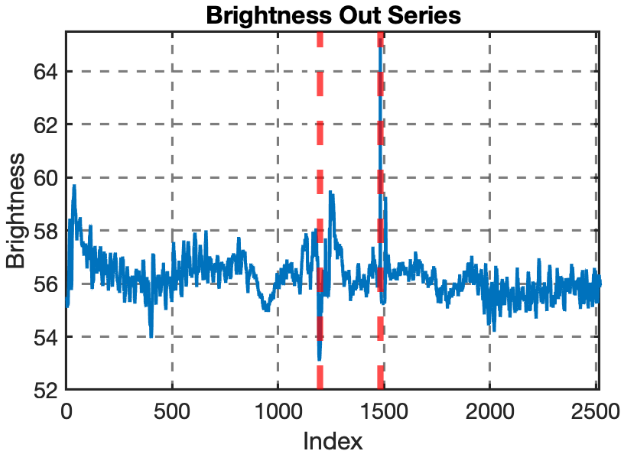


Figure 5.8 Brightness out from the D0 stage, used to produce the prediction residuals in Figure 5.7. Index 1297, and index 1482 have been indicated with the vertical lines.

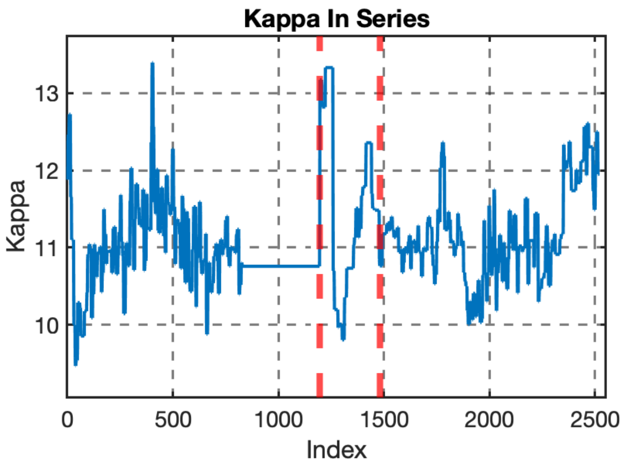


Figure 5.9 Incoming kappa to the D0 stage, used to produce the prediction residuals in Figure 5.7. Index 1297, and index 1482 have been indicated with the vertical lines. The kappa meter seems to be malfunctioning in the time leading up to index 1297, and shortly after 1297 the kappa measurement peaks. The kappa measurement at index 1482 does not indicate any abnormal kappa levels. It can therefore be seen that there is no peaks or drops in kappa at the investigated indices.

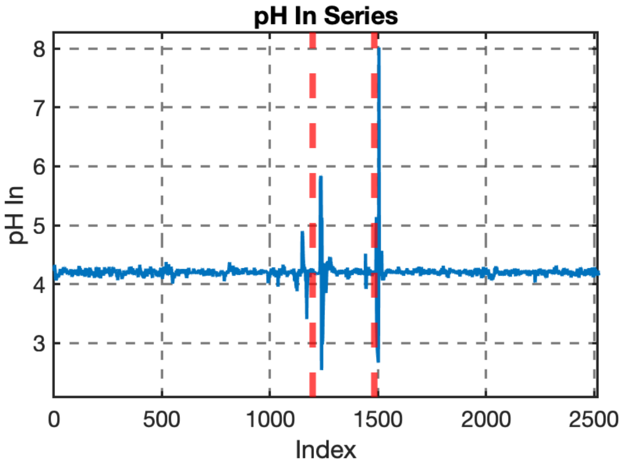


Figure 5.10 Incoming pH to the D0 stage, used to produce the prediction residuals in Figure 5.7. Index 1297, and index 1482 have been indicated with the vertical lines. There are no large peaks or drops at either of the indices, but there can be seen to be a peak in pH some time after index 1482.

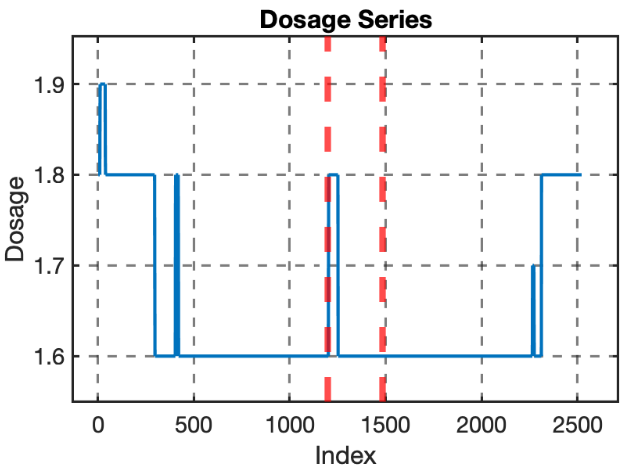


Figure 5.11 The kappa factor κ for dosage to the D0 stage, used to produce the prediction residuals in Figure 5.7. Index 1297, and index 1482 have been indicated with the vertical lines. Shortly after index 1297 there is a increase in dosage, and no change in dosage happens at index 1482.

5.2 Do the coefficients of the models follow theory?

Theory says that increasing bleaching chemical dosage should have a diminishing effect as the dosage is raised. This suggests that for the bleaching chemical dosage variable, the first order coefficient should be positive, and the second order coefficient should be negative, since this represents a diminishing brightness increase as the dosage is increased.

Since interaction terms possibly could affect the sign of the coefficients, no interaction terms were used when evaluating the sign of the coefficients. The three inputs that were used was bleaching chemical dosage, and the pH and brightness of the incoming pulp. For the D0 stage kappa was used instead of brightness. The output variable for all stages was outgoing pulp brightness.

What was found was that the correct sign of the coefficients only was achieved in some cases. When including pH as a input, it was for the models fitted on the Combined 23 dataset, only achieved for the D1 model. For the D0 model both coefficients were positive and for the D2 model both coefficients were negative. When excluding pH, and only using dosage and incoming kappa for D0 or brightness for D1 and D2, the coefficients had the correct sign in all models. What this meant is that when including pH, there is no decreasing efficiency when increasing dosage in D0. A decreasing efficiency is expected, see Figure 2.2.

The negative coefficients means for D2 that the brightness is expected to increase when dosages are lowered. This is counter intuitive since the purpose of increasing dosages are to increase the brightness. What was revealed though when doing the process evaluation in Chapter 7, was that the dosages in D2 had been larger for incoming pulp with a higher brightness, while the outgoing pulp's brightness was constant. This explains the negative coefficients, but does not fully explain why the coefficients turned positive when pH of incoming pulp was excluded. The three inputs were plotted against each other in Figure 5.12. What can be seen is that the pH does not have any clear effect on the other variables or the brightness increase. As discovered in Chapter 7, the dosages can be seen to be higher for incoming pulp with higher brightness. The dosages are controlled by the process operators, see Section 2.5. This means that it is possible that the dosage or incoming pulp brightness are colliders, affecting each other. Since it was revealed that the brightness sensor after the D2 stage has difficulties measuring brightnesses above a certain level, it is possible that the higher dosages for the higher incoming pulp brightnesses was to achive a brightness outside the range of the brightness sensor. To investigate this further, research into the reasoning among the operators for changing the dosages would be needed.

Since including pH gave the best results in terms of RMSE, models using pH were continued to be used. If one would want to use the models for optimization, it has to be noted though that for example in the optimization step in the pulp tracking program, models without pH probably need to be used to capture the decreasing bleaching efficiency of a larger dosage.

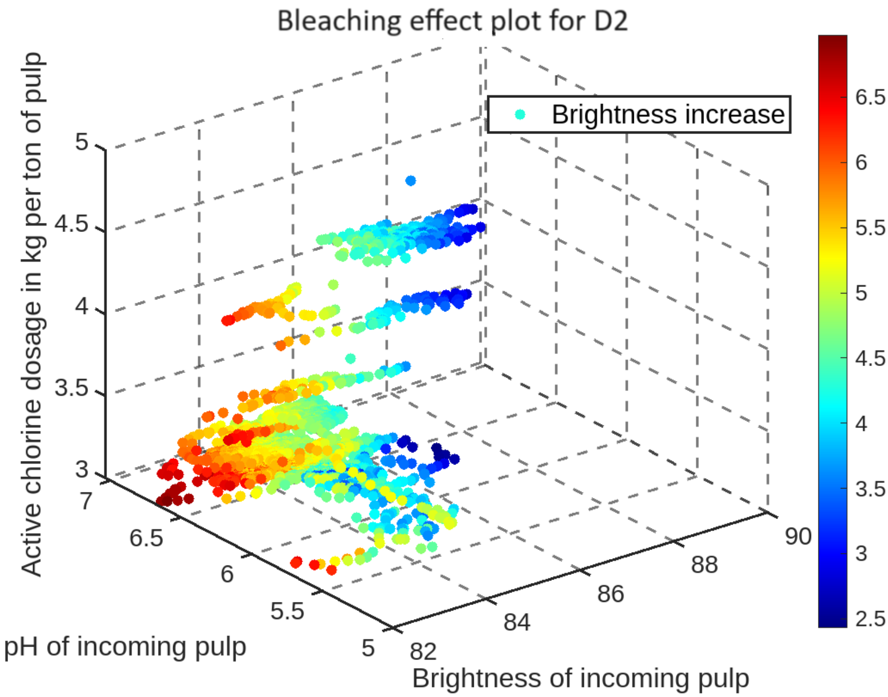


Figure 5.12 The input variables for the D2 stage, with the colorbar displaying the brightness increase. The data is from the March 2024 dataset. It can be seen that the dosages are larger for higher brightness in the incoming pulp. This is the same effect seen in Figure 7.7. The brightness increase can be to be larger when the brightness of the incoming pulp is lower, the same effect as seen in Figure 7.6. The pH of the incoming pulp does not seem to have any clear effects on the brightness increase, or the other variables.

6

Bleaching control decision support system

The fitted models from Chapter 5 are in this chapter implemented in a graphical user interface using excel to create a decision support system for setting the bleaching chemical dosages for each D-stage.

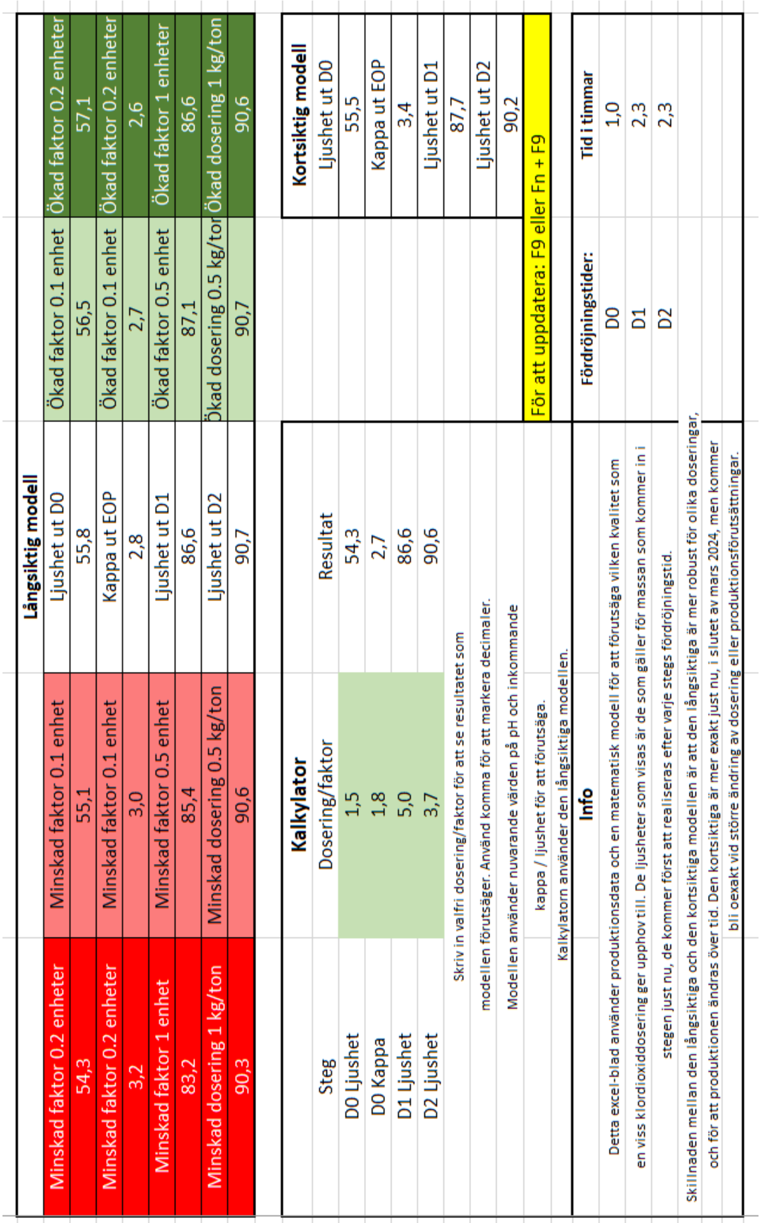
6.1 User interface

In Microsoft Excel, a decision support system was created using the fitted models M1 and M2. M1, which is trained on the `Combined 23 + March 2024` dataset, was named the long-term model in the user interface. This is because it was trained on more data than M2, which was trained on only the `March 2024` dataset, and subsequently named the short-term model. Since the long-term model is trained on more data, it is more robust, but with the drawback of being less accurate in the short term. The short-term model is more accurate in the short term, but will deteriorate faster, and also cannot handle large changes in dosage. The purpose of the short-term model is to represent an adaptive model that would be continuously re-trained on new production data.

The decision support system presents the predicted qualities based on the current production data and hypothetical chemical dosages. It displays the predicted effects of changing the dosages in each stage, both with set intervals of dosage changes and a calculator for setting custom dosages. The system does not employ any pulp-tracking, meaning that the predictions for the stage's output will have a delay before they are realized. The approximate delays are retrieved from the plant control system and also presented in the system view.

What can be seen in the upper part of Figure 6.1 is the predicted effects of changing the dosages in each stage with set intervals of dosage changes. Red represents lower dosages, and green increased dosages. The white cells in the middle are what the system predicts the future qualities will be with the current dosages. Below it, to the left, the calculator for setting custom dosages can be seen. Here, the operator can input a custom dosage, and based on the current production data, the predicted quality is calculated. To the right of the calculator, the predictions from the short-term model M2 are presented. No predicted qualities from changed dosages are presented, this is because the short-term models perform worse on dosages that differ from the data it were trained on. Below the short-term model predictions, the estimated delays for each stage are presented. This is just a rough estimate based on the production rate, and does not use any pulp tracking. The purpose is to help the user to know when the predicted qualities will have effect.

Since the model for D2 was seen to predict lower brightness increases when increasing dosages, this also happens for the predictions in the program. In Figure 6.1, the predicted brightness for increasing the dosages in D2 can be seen to decrease, when it should probably just stay constant. A risk is that a non-reasonable prediction lowers the trust in the models overall. See Section 5.2 and Chapter 7 for more about the D2 models and data.



		Långsiktig modell		
Minskad faktor 0.2 enheter	Minskad faktor 0.1 enhet	Ljushet ut D0	Ökad faktor 0.1 enhet	Ökad faktor 0.2 enheter
54,3	55,1	55,8	56,5	57,1
Minskad faktor 0.2 enheter	Minskad faktor 0.1 enhet	Kappa ut EOP	Ökad faktor 0.1 enhet	Ökad faktor 0.2 enheter
3,2	3,0	2,8	2,7	2,6
Minskad faktor 1 enhet	Minskad faktor 0.5 enhet	Ljushet ut D1	Ökad faktor 0.5 enhet	Ökad faktor 1 enheter
83,2	85,4	86,6	87,1	86,6
Minskad dosering 1 kg/ton	Minskad dosering 0.5 kg/ton	Ljushet ut D2	Ökad dosering 0.5 kg/tor	Ökad dosering 1 kg/ton
90,3	90,6	90,7	90,7	90,6

	Kalkylator	
Steg	Dosering/faktor	Resultat
D0 Ljushet	1,5	54,3
D0 Kappa	1,8	2,7
D1 Ljushet	5,0	86,6
D2 Ljushet	3,7	90,6

Skriv in valfri dosering/faktor för att se resultatet som
modellen förutsäger. Använd komma för att markera decimaler.
Modellen använder nuvarande värden på pH och inkommande
kappa / ljushet för att förutsäga.
Kalkylatorn använder den långsiktiga modellen.

Kortsiktig modell
Ljushet ut D0
55,5
Kappa ut EOP
3,4
Ljushet ut D1
87,7
Ljushet ut D2
90,2

För att uppdatera: F9 eller Fn + F9

Info

Detta excel-blad använder produktionsdata och en matematisk modell för att förutsäga vilken kvalitet som
en viss klordioxiddosering ger upphov till. De ljusheter som visas är de som gäller för massan som kommer in i
stegen just nu, de kommer först att realiseras efter varje stegs fördröjningstid.
Skillnaden mellan den långsiktiga och den kortsiktiga modellen är att den långsiktiga är mer robust för olika doseringar,
och för att produktionen ändras över tid. Den kortsiktiga är mer exakt just nu, i slutet av mars 2024, men kommer
bli oexakt vid större ändring av dosering eller produktionsförutsättningar.

Fördröjningstider:	Tid i timmar
D0	1,0
D1	2,3
D2	2,3

Figure 6.1 Decision Support System created in Microsoft Excel for setting bleaching chemical dosages.

7

Process evaluation

To find possible improvements for the bleaching process, the Combined 23 dataset produced by the pulp tracking program is analyzed in aspect of bleaching efficiency.

7.1 Method

Comparing the bleaching stages efficiency is not totally straightforward. This is because the D0 stage is focused on lowering the amount of lignin in the pulp, while the D1 and D2 stages are focused on increasing the brightness. The amount of lignin in the pulp after the D0 stage is, however, still linked to the later stages ability of increasing the pulp's brightness. This enables some comparisons, which have been measured in the relative increase in quality per amount of added bleaching chemical. In order to have a measure of the effectiveness of the stages, some simple models were fitted to the data. One linear model of the type $y = ax + b$, and one quadratic of the type $y = ax^2 + bx + c$. The models were fitted using MATLABs, [The MathWorks Inc., 2020b], `polyfit` command. The fitted models are plotted in Figures 7.1 to 7.6.

7.2 Data preparation

Since the D0 stage has a kappa sensor as a measure of incoming quality, and a brightness as a measure of outgoing quality, the kappa sensor after the EOP stage was used instead as measurement of outgoing quality. This was to be able to directly compare the incoming and outgoing kappa, since no direct conversion between brightness and kappa existed. Since the bleaching chemical dosages in the EOP stage is constant, the effect of the EOP stage should be constant. For the other stages, D1 and D2, the difference in brightness was used. For the D1 stage, the brightness after the D0 stage was used, since no measure of brightness existed after the EOP stage. The bleaching chemical dosage in the Combined 23 dataset was in the form of kappa factor for the D0 and D1 stage, and in kg active chlorine per ton pulp for the D2 stage. To be able to compare better, the kappa factor for the dosage inputs to the D0 and D1 stages was recalculated in kg active chlorine per ton pulp. This was done by taking the relevant kappa measurement for each stage, and multiplying it by the kappa factor to get the dosage in kg active chlorine per ton pulp.

7.3 Results

When observing the plots for the linear model, Figures 7.1, 7.3 and 7.5, and coefficients in Table 7.1, it can be noted that they have different slopes. The pulp quality increase for the D0 stage can be seen to increase when the amount of added bleaching chemical is increased. For the D1 stage, the pulp quality increase remains almost constant, and for the D2 stage, the stage quality increase decreases when the chemical dosage is increased. When using quadratic models, with coefficients in Table 7.2, the D2 model can be seen in Figure 7.6 to remain almost linear. The D0 model can be seen in Figure 7.2 to flatten out for higher dosages. The quadratic D1 model can be seen to have a parabolic shape in Figure 7.4.

The results for the D0 stage follow what could be expected from theory, with the quadratic curve similar to the theoretical ones in Figure 2.2. The largest increase in the stage's quality increase can be seen in the range of 15 to 25 kg of active chlorine per ton of pulp, with the curve flattening out after that.

The data for the D1 stage can be seen to be quite compact, without any visible structure. Although, since there are a lot of datapoints, judging the data visually can be misleading. The fact that the quadratic model indicates that the stage's pulp quality increase peaks in the middle of the data is interesting. It is possible that the drop after the peak is due to some outlier data present, since a line of low efficiency measurements can be noted at a dosage of 16 kg per ton.

What can be noted, though, is that the data for the D2 stage efficiency follows a negative trend too. In order to find the cause of this, the other data available for the D2 stage was examined. In Figure 7.7, the incoming pulp's brightness is plotted against the amount of bleaching chemical that was added. It can be seen that there appears to be a trend where higher incoming pulp brightnesses has a higher dosage. When discussing this with plant staff, it was revealed that the brightness of the pulp is also measured after the pulp has left the bleaching plant, with a more sensitive sensor. This measurement is performed when the pulp is dried, and can be several hours after the pulp has left the bleaching plant. When comparing to the brightness of the outgoing pulp in Figure 7.8, the brightness can be seen to not have the same trend for increasing dosage. This is thus because the sensor after the D2 stage can not measure the highest brightnesses. This could thus explain the decreasing efficiency for the D2 stage in Figures 7.5 and 7.6, since the outgoing brightness caps out at around ISO 90, regardless of the bleaching dosage. A higher incoming brightness will therefore have a lower quality increase, since it already is close to the maximum brightness that the sensor can measure.

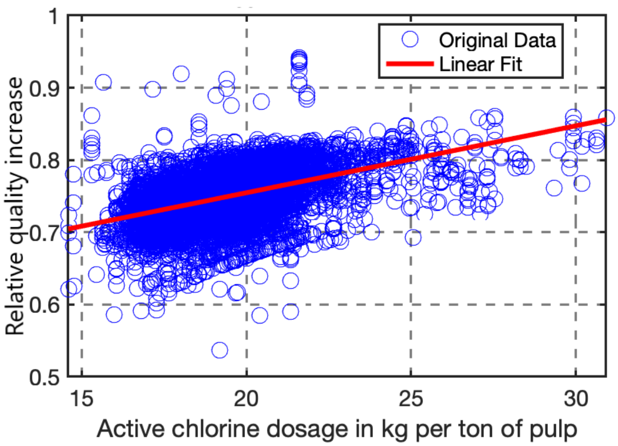


Figure 7.1 The figure shows the quality increase in the pulp in the D0 stage, for different amounts of chlorine dioxide dosages, measured in kg active chlorine per ton of pulp. The relative quality increase is defined as the decrease in kappa divided by the incoming pulp's kappa. To this data, a line has been fitted, with coefficients according to Table 7.1.

Table 7.1 The coefficients from the fit of linear models across the stages. The confidence intervals of the fit are also presented.

Stage	Parameter	Coefficient	95% Confidence Bounds
D0	a	0.093	(0.009, 0.010)
	b	0.57	(0.56, 0.58)
D1	a	0.0037	(0.0029, 0.0050)
	b	0.51	(0.51, 0.51)
D2	a	-0.018	(-0.018, -0.017)
	b	0.12	(0.12, 0.12)

In summary, only the D0 stage has a clear benefit of increasing the dosage, with both linear and quadratic models indicating a larger quality increase with greater dosage. The quadratic model for the D1 stage indicates that there could be an increasing quality increase up to a peak at a dosage of around 12 kg active chlorine per ton pulp, while the linear model is almost constant. The D2 models need better data, since the highest brightnesses in the pulp can not be measured by the sensor used to model.

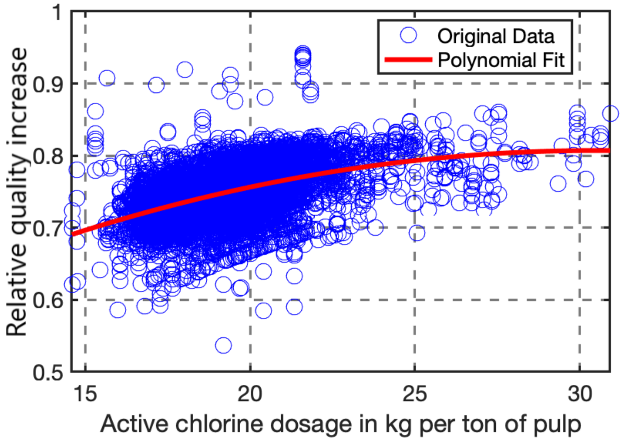


Figure 7.2 The figure shows the quality increase in the pulp in the D0 stage, for different amounts of chlorine dioxide dosages, measured in kg active chlorine per ton of pulp. The relative quality increase is defined as the decrease in kappa divided by the incoming pulp's kappa. To this data, a quadratic curve has been fitted, with coefficients according to Table 7.2.

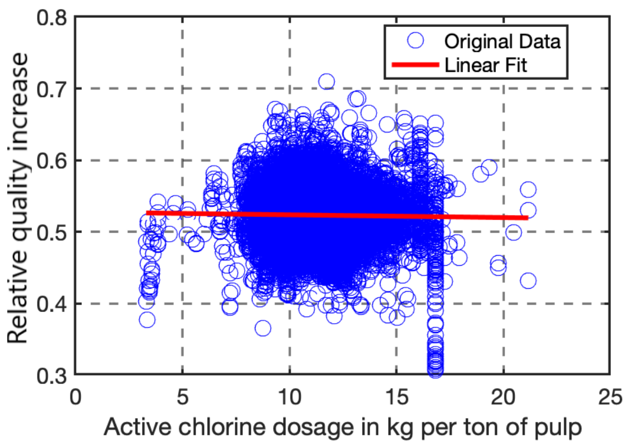


Figure 7.3 The figure shows the quality increase in the pulp in the D1 stage, for different amounts of chlorine dioxide dosages, measured in kg active chlorine per ton of pulp. The relative quality increase is defined as the increase in brightness divided by the incoming pulp's brightness. To this data, a line has been fitted, with coefficients according to Table 7.1. At a dosage of around 16 a line of datapoints can be seen to be irregular. This is likely due to a malfunction sensor, but was not investigated further.

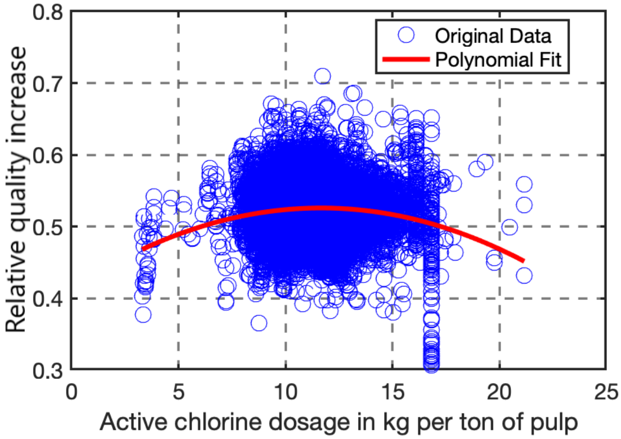


Figure 7.4 The figure shows the quality increase in the pulp in the D1 stage, for different amounts of chlorine dioxide dosages, measured in kg active chlorine per ton of pulp. The relative quality increase is defined as the decrease in kappa divided by the incoming pulp's kappa. To this data, a quadratic curve has been fitted, with coefficients according to Table 7.2.

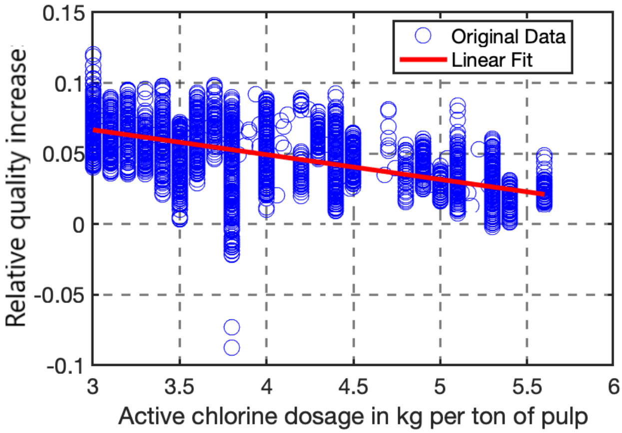


Figure 7.5 The figure shows the quality increase in the pulp in the D2 stage, for different amounts of chlorine dioxide dosages, measured in kg active chlorine per ton of pulp. The relative quality increase is defined as the decrease in kappa divided by the incoming pulp's kappa. To this data, a line has been fitted, with coefficients according to Table 7.1.

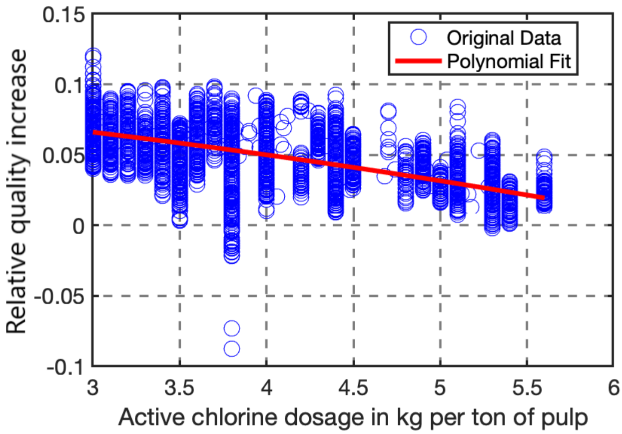


Figure 7.6 The figure shows the quality increase in the pulp in the D2 stage, for different amounts of chlorine dioxide dosages, measured in kg active chlorine per ton of pulp. The relative quality increase is defined as the decrease in kappa divided by the incoming pulp's kappa. To this data, a quadratic curve has been fitted, with coefficients according to Table 7.2.

Table 7.2 The parameters from the fit of quadratic models across the stages. The confidence intervals of the fit are also presented.

Stage	Parameter	Coefficient	95% Confidence Bounds
D0	a	-0.00046	(-0.00054, -0.00038)
	b	0.028	(0.025, 0.031)
	c	0.38	(0.35, 0.41)
D1	a	-0.082	(-0.084, -0.080)
	b	0.66	(0.64, 0.70)
	c	-0.78	(-0.82, -0.75)
D2	a	-0.0012	(-0.0015, -0.0008)
	b	-0.010	(-0.011, -0.005)
	c	0.10	(0.01, 0.11)

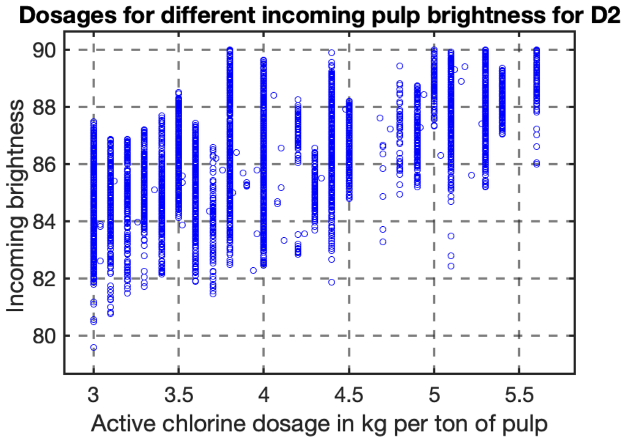


Figure 7.7 The figure shows the brightness of the incoming pulp to the D2 stage, against the dosage of chlorine dioxide, measured in kg active chlorine per ton of pulp.

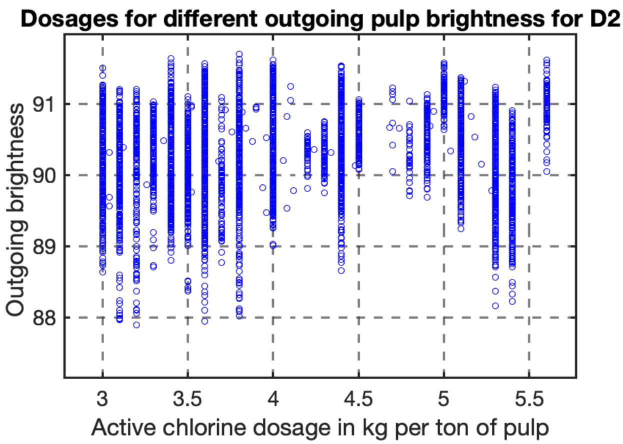


Figure 7.8 The figure shows the brightness of the outgoing pulp to the D2 stage, against the dosage of chlorine dioxide, measured in kg active chlorine per ton of pulp.

8

Discussion

In this chapter, aspects of the implementation are discussed. Some thoughts about how an improved control system could work are presented, and also some other suggestions for future work.

8.1 The plug flow approximation and delay estimation

As described in Section 1.3, handling the varying delay is a main challenge with this type of process, and the solution was the plug tracking program. A fundamental part of it was approximating the pulp as discrete plugs. Since [Tessier et al., 2000] found that there is less plug flow and more blending when the concentration of the pulp is lower, the true process probably is not a pure plug flow. Since the D-stages are built for plug flow, and have a high pulp concentration, the model is most valid for these stages. The E-stages also have a high concentration in the upper part of the stage, but by dilution with water in the lower part of the stage, the concentration is lowered. This means that there will be some blending of the pulp in the stage. The effect of this blending on the validity of the plug flow is partly mitigated through the sample time of five minutes, since any blending that is faster than that is within the plug. The E-stages also had a higher variance in the volume estimations, than the D-stages. Since an error in the volume estimation will lead to errors in the datasets and subsequently the models, this will have some effect. It is known that the amount of pulp in the E-stages varies due to the stage fill height, although no clear effect was found when including it in the volume estimates.

8.2 The datasets

The great value of a factory diary

The data selection process began by choosing suitable time periods, as described in Section 3.3. This was done both by looking at whether the data from all the sensors were complete, but also by investigating the factory diary. What could be found in it were, for example, notes about sensors malfunctioning, properties of the pulp that were out of the normal, and reasons for changing bleaching chemical dosages. This enabled a more accurate data selection process, that would not have been possible by just looking at the data alone. The value of the diary highlights the importance of a functioning data labeling structure in order to enable data-based methods. If the diary were even more detailed, with a future data-scientist interest in mind, instead of being mainly focused on internal communication and logging, it could have contributed even more.

Data preparation

The raw production data from the selected time periods was used in the pulp tracking program. The datasets created by the program, mainly the Combined 23 dataset, were then used for both the decision support program, and the process evaluation, without any particular data preparation being performed. This meant that the data was not analyzed for outliers, filtered or in any other way altered to increase performance. The reason for this was both that it was not permitted due to time constraints, but also to demonstrate what could be achieved with limited data preparation. It is possible that better results from the models in Chapter 6, or conclusions about the production in Chapter 7, could have been achieved with more data preparation. What it would have needed, though, is knowledge about what data that could be expected to be normal, and what not.

8.3 The process evaluation

What the process evaluation showed was a clear pattern for the bleaching efficiency when increasing dosage in the D0 stage. This can be used as a tool when deciding on the dosages to set in stage in the future. For the D1 stage, the results were a bit unclear, due to the data lacking a structure. The D2 stage could be seen to reach the same brightnesses regardless of the dosage applied. This was explained to be due to the sensor measuring the brightness not being able to record the highest pulp brightnesses. It is still possible that there are some possible reductions in dosage to be had. Since the highest pulp brightnesses are not measured directly after the bleaching stage, there is a risk that too high of a dosage is used, to compensate for the even longer delay times that comes with using sensor further along the production line in the pulp plant. When decreasing the dosages, and moving closer to the limits of the process, the risk of bleaching too low increases though. It is therefore still important to maintain some safety margin since the cost of producing bad quality pulp is high. To get an approximate figure of the possible savings, the calculations for the cost of bleaching in Section 2.6 can be used. A possible reduction of dosage in D2 of 2 kg active chlorine per ton, equates to a reduction of chlorine dioxide usage in the bleaching plant of 5 %. If the cost of bleaching in the D-stages mainly come from chlorine dioxide, then the possible savings would be around 4

MSEK per year. The plausibility of lowering the dosages this way needs to be further investigated though, and it is also possible that a more accurate sensor needs to be installed directly after D2 to be able to verify the plausibility of lowering dosages.

8.4 The control system

Operators as controllers

The benefit of a human operating the process seems to be robustness and communication. An example given was that when an anticipated batch of low-quality pulp was going to enter the bleaching plant, the operators in the previous parts of the process could communicate this to the bleaching plant operator, which in turn could compensate with higher dosages. The operators also seem to develop a feeling for the process over time, knowing roughly when to change dosages and how much. The operator can be seen as a feedback controller, since if the brightness out of a stage gets too low or high, then the operator will change the dosages. With the current control system, though, there are no predictions for the outgoing pulp, meaning that error compensation cannot be performed until it is seen. This probably leads to unnecessary large dosages to not have a too low pulp brightness out of the bleaching plant. This could be seen in the process evaluation for the D2 stage, and is something that a model-based control system could mitigate by predicting the future pulp brightness.

Introducing a model-based control solution

Trust in the models. The results from the decision support system models in Chapter 5 show what accuracy that can be expected from the models, on new data, without any extensive data preparations. Whether this accuracy is enough, or not, is a matter of trust in the model. The RMSE of the predictions were all within the tolerated error for the measured value, indicating that they are good enough. But it could perhaps be worse if they sometimes are really wrong, even though they are accurate in terms of RMSE. The interface for the decision support system created in Chapter 6 could be used as a tool for gauging this trust. By running it side by side with the production, the operators could see how it performs in real time. Evaluations could include which kind of production conditions it manages to predict well, and which it does not. The results from an evaluation like that could be a part of a decision basis for a full-scale solution.

Proposed control design. If the models are deemed to be trusted, a new control solution could be implemented based on models like them, with or without adaptation to new data. What is evident is that the D1 and D2 models achieved the best results on new data, see Table 5.1. Since the current available measurement for incoming pulp kappa to D0 is slowly sampled, a possible new automatic control solution could be to keep the kappa factor control for D0, and use a model-based control solution for D1 and D2. This could perhaps tackle some challenges that exist when controlling the plant today, see end of Section 2.5. Challenge 1, the problem of not seeing the result of a change in dosage until the pulp has passed through the stage, would be mitigated by predicting the result. This probably means less safety marginal in the D2 stage would be needed, making the bleaching plant more efficient. Process disturbances could also be compensated for faster, thanks to the continuous measurements that are available for the D1 and D2 stages. This means that challenge 2, the slow sampling of kappa before D0, would be less of a problem since the D1 and D2 stages could compensate for any disturbance. Challenge 3, that the bleaching of the pulp sometimes is less effective in D0, hopefully also can be mitigated with the fast compensation in D1 and D2. It is possible, though, that some kind of extra compensation could be needed. For example, if the kappa number after D0 is extra high, the models for D1 and D2 could get overridden with an extra high dosage to not get a too low brightness out of the bleaching plant.

The negative aspect of a model-based control system would be that some kind of data gathering system would be needed to be implemented, to keep the models updated. An operator would still be needed for events or disturbances out of the ordinary, and with an automatic control solution, the operator possibly would not get the same intuition about the process to be able to handle those cases. The control system could either be designed to optimize the dosages for efficiency according to the models, or to hold some set point. For example, since the process evaluation for the D2 stage indicated that low chemical dosages in D2 could increase the brightness adequately for quite low incoming pulp brightnesses, the D1 output brightness could be set to this lower level. This would be some kind of manual optimization, with the benefit of being understandable and transparent, something that could be important to gain trust among the process operators.

8.5 Future work

The volume estimation

For future work, the variance of volume estimates for the E-stages would be interesting to explore. Testing other sample times, to perhaps limit the effect of the non-plug flow, could also be worthwhile.

Gathering more data for the stage evaluation

For future work, there could be a benefit of finding new data for the stage evaluation. For example, finding the limits of the D2 stage by bleaching pulp with even lower brightness than in this study. Furthermore, trying to get more useful data for the evaluation of the D1 stage would be interesting, as it was difficult to draw conclusions from this study's data.

Adaptive models

What can be observed from the model evaluation results in Section 5.1 is that the models, trained on data close in time to the time of the predictions, perform better. This is reasonable since the process conditions can be expected to vary, both in terms of pulp properties and sensor calibrations. The results also indicate that a robust amount of data is needed to make reliable predictions for a change in dosage rate, while at the same time staying calibrated to the current process conditions. A solution to this is some way of adaptation, and several techniques could be used. A form of decaying adaptation, where recent data was given more importance and continuously added to the models, was used for an implementation by Tessier et al. [Flisberg and Rönnqvist, 2007]. The adaptation does not necessarily have to be continuous though, for example, new data could manually be gathered each month and added to the models.

Regardless of adaptation time frame, some challenges need to be solved to implement adaptation. Primarily, a systematic way of data gathering needs to be in place. The more continuous and automatic the gathering is, the more robust it has to be. This means identifying and handling periods when the data is unreliable, for example during process disturbances or when sensors fail. Secondarily, the domain of validity for the models needs to be accounted for. What could be seen in the results, was that the March 24 model could not handle changes in dosage very well, giving unreliable predictions. This is a symptom of a limited domain of validity, which likely is due to the small amount of training data, and in turn the range of bleaching chemical dosages that the model was trained on. The optimal amount of historical data that the models should train on could thus be varying, depending on what range of dosages that can be found in the data.

9

Conclusions

From this thesis, a few conclusions can be made:

- It is possible to model the bleaching stages using polynomial models and existing production data. Without extensive data preparation, the accuracy of the models is within the error margins of the sensors. The results are valid for the value ranges that existed in the used data, for example, ranges of bleaching chemical dosages or brightness of the pulp.

- Handling the delay through the used method of volume estimation and pulp tracking enabled creation of the datasets used to fit the polynomial models. Their performance validates the pulp tracking method. However, the method could be improved by better volume estimations for the E-stages.

- Pulp tracking enables process diagnostics opportunities by connecting input and output data for the stages. Since the results for the D1 stage were difficult to tell anything from, the method probably can be improved, or further evaluated with new data. The results from D2 point to possible savings, although it needs further investigation.

- In the future, an improved control solution could be based on the model structure that were used in this thesis.

Bibliography

Billerud (2024). URL: https://www.billerud.se/om-billerud/vara-produktionsanlaggningar/karlsborg#:~:text=I%20Karlsborg%20tillverkar%20vi%20s%C3%A4ckpapper,utveckling%20av%20p%C3%A5sar%20och%20s%C3%A4ckf%C3%B6rpackningar. (visited on 2024-04-20).

Dahlbäck, M. (2020). *Evaluation of models for process time delay estimation in a pulp bleaching plant.*

de Oliveira, M. H. (2022). "Use of model predictive control to optimize the kraft-bleaching process". *Paper to Export.* URL: https://papertoexport.com/kraft-bleaching-process/ (visited on 2024-04-20).

Flisberg, P. and M. Rönnqvist (2007). "Optimized on-line process control of bleaching operations with optcab". *NHH Dept. of Finance & Management Science Discussion Paper* **09**.

Gellerstedt, G. (2009). "9. chemistry of bleaching of chemical pulp". In: Ek, M. et al. (Eds.). *Volume 2 Pulping Chemistry and Technology*. De Gruyter, Berlin, New York, pp. 201–238. ISBN: 9783110213423. DOI: doi:10.1515/9783110213423.201. URL: https://doi.org/10.1515/9783110213423.201.

Jung, A. (2022). *Machine Learning. The Basics.* Machine Learning: Foundations, Methodologies, and Applications. Springer Nature Singapore, p. 120. ISBN: 9789811681929. URL: https://ludwig.lub.lu.se/login?url=https://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,uid&db=cat02271a&AN=atoz.ebs30578841e&site=eds-live&scope=site.

Kassberg, M. (1996). *Blekning*. Skogsindustrins Utbildning i Markaryd AB. ISBN: 9173221864.

Ljung, L., T. Glad, and A. Hansson (2021). *Modeling and Identification of Dynamic Systems*. Studentlitteratur AB, Lund. ISBN: 9789144153452.

Mori, Y., M. Watanabe, and T. Yamamoto (2014). "A multivariable pulp brightness control of ecf bleaching process by model predictive control". *Japan Technical Association of the Pulp and Paper Industry* **68**:10, pp. 1184–1195. DOI: 10.2524/jtappij.68.1184.

Process knowledge (2024). Personal communications. Process information from the plants internal documents and interviews with Billerud Karlsborg staff during spring 2024.

Ragnar, M., G. Henriksson, M. E. Lindström, M. Wimby, J. Blechschmidt, and S. Heinemann (2014). "Pulp". In: *Ullmann's Encyclopedia of Industrial Chemistry*. John Wiley & Sons, Ltd, pp. 1–92. ISBN: 9783527306732. DOI: https://doi.org/10.1002/14356007.a18_545.pub4. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/14356007.a18_545.pub4. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/14356007.a18_545.pub4.

Tessier, P., M. Savoie, and M. Pudlas (2000). "Industrial implementation of an advanced bleach plant control system". *Tappi Journal* **83**, pp. 139–143.

The MathWorks Inc. (2020a). *Fitlm documentation*. Natick, Massachusetts, United States. URL: https://se.mathworks.com/help/stats/fitlm.html.

The MathWorks Inc. (2020b). *Matlab version: '9.9.0.2037887 (r2020b) update 8'*. Natick, Massachusetts, United States. URL: https://www.mathworks.com.

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Title and subtitle
Improving the Efficiency of a Pulp Bleaching Plant through Data-Based Modeling

Abstract

The kraft pulp bleaching process presents significant operational challenges due to its inherent non-linear reactions and unpredictable delays, complicating effective control and optimization. This thesis aims to improve the efficiency of the process through modeling it, and lays the groundwork for a new and improved automatic model-based control system. It explores a way of handling the varying delay by tracking the pulp throughout the process. This enables modeling of the chemical reactions using parameterized static models, fitted to existing production data. The models are used to create a decision support system to predict the future pulp quality from the bleaching process. The system showcases the possibilities of using modelbased control to increase the efficiency of the plant. The pulp tracking also enables an evaluation of the current process, since it links input data to output data for the process.

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