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Evaluation and improved control of a TCF bleaching plant

Master's thesis in Systems, Control and Mechatronics
Performed at BillerudKorsnäs in Frövi

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Abstract

Control of bleaching plants is a complex task that requires a wide variety of control structures. The processes are often multivariate and dead-time dominating which emphasizes the need of a Model Predictive controller (MPC). The base of these controllers are the models and it is thus of importance that they are accurate. This thesis work has been conducted at BillerudKorsnäs Pulp and Paper mill in Frövi where the performance of the MPCs used for the bleaching are inadequate. The goal of this thesis has been to generate new models for these as well as to improve the control of other processes in the bleaching plant. The System Identification toolbox in Matlab has been used to generate models for the delignification stage based on input and output data. The data has been generated by several performed trials. Only one new model, which describes the relation between added $NaOH$ and pH, has been generated. It has not been possible to generate other models for the MPCs due to many underlying problems. A faulty subcontroller which regulates the flow of oxygen has been discovered. New PI parameters have been suggested for intermediate tanks to smoothen the level control. It has finally been concluded that, in order to improve the performance of the MPCs, a large scale project must be conducted that focuses on all parts of the bleaching plant.

Keywords: Model predictive control (MPC), pulp and paper bleaching, System Identification, Pseudo Random Binary Signal (PRBS)

Notations

Abbreviations

CV Controlled Variable

DV Disturbance Variable

DRP Double Rectangular Pulse

ECF Elemental Chlorine-Free

IPDT Integrator Plus Dead Time

MV Manipulated Variable

MPC Model Predictive Control

OP Operating Point

PV Process Values

PRBS Pseudo Random Binary Signal

RMS Root-Mean-Square

SP Setpoint

TCF Totally Chlorine-Free

Chemicals

ClO_2 Chlorine Dioxide

EDTA Ethylenediaminetetraacetic Acid

H_2O_2 Hydrogen Peroxide

NaOH Sodium Hydroxide

O_2 Oxygen

O_3 Ozone

Contents

1 Background

The pulp and paper industry has been a big part of the Swedish industry since the 19th century, and before world war one Sweden was the biggest exporter of pulp in the world [1]. Even though it is still among the largest producers of pulp, other countries such as the USA and China has surpassed Sweden [2].

Production of paper products is a complex process that requires many different steps [3]. First the lumber has to be worked into smaller parts, called chips. These chips are then processed into paper pulp. Pulp is the separated cellulose fibres from wood or other similar fibrous materials. There are two ways to separate the pulp, mechanically or chemically. These two methods can be combined as well. Mechanical pulp is produced by grinding the chips and thus reducing them to fibres. Chemical pulp is produced by cooking the chips together with chemicals, breaking down the lignin that binds together the fibres [4]. The produced pulp is of a brown colour but some final products are desired to be white. The pulp is bleached with different chemicals to achieve a satisfactory brightness. There are several ways to bleach the pulp. However the most common way historically has been to bleach with chlorine [5]. Due to the negative environmental effects of chlorine, other chemicals have replaced it in some productions. Plants that do not bleach with chlorine are called Elemental Chlorine-Free (ECF) or Totally Chlorine-Free (TCF). In ECF processes the chlorine is replaced with chlorine dioxide (ClO_2) and in TCF plants it is replaced with chemicals that are completely free of chlorine [6]. Hydrogen peroxide (H_2O_2) or ozone (O_3) are used as the main bleaching agents in these plants [6].

Control of large industrial processes such as pulp and paper industries is a complex task that requires a wide variety of control structures [7]. The aim of those control structures is to guarantee that the end product satisfies certain criteria. In a bleaching plant the criteria would be to minimize the chemical consumption, without lowering the brightness of the end product, as well as to minimize the variability of the end product [8]. Achieving these goals would not only benefit the company by decreasing the cost, but it would also benefit the environment. The processes are multivariable and dead time dominating, which emphasizes the need of a Model Predictive Controller (MPC) [7]. An MPC is a controller that calculates an optimal control strategy based on predicted future outputs and by minimizing a cost function. These calculations are reapeted at every time instance [9]. The foundation of an MPC is the models describing the system. It is thus of great importance that these model are accurate. The main focus of this thesis is to improve the models used at the bleaching plant at BillerudKorsnäs pulp and paper plant in Frövi for the MPCs.

1.1 Bleaching processes at BillerudKorsnäs, Frövi

This thesis work has been conducted at the bleaching plant of BillerudKorsnäs' pulp and paper mill in Frövi. The bleaching plant is of a TCF type and the main chemical used for bleaching is H_2O_2. However, other reactions have to occur before the peroxide stage in order to achieve satisfactory bleaching. The entire plant consist of five reactors and one tank that acts as a reactor. These are placed in a serial configuration. The plant can also be divided into three parts that serve different purposes. The parts are a delignification stage, a chelating stage and the previously mentioned bleaching stage. The entire bleaching plant is presented in Figure 1.1.

The first part is the delignification stage (O) which consist of two reactors. The goal of the O-stage is to further remove lignin bound to the pulp [10]. Lignin is the main contributor to the brown color of the pulp which makes this step essential [6]. Reactive oxygen is used to remove the lignin in the O-stage. However, oxygen is not selective, meaning that it will also break down the pulp [10]. Therefore there is a balance between how much lignin that is removed and how large the yield is. The reaction also affects the strength of the pulp negatively. Since oxygen is a stable molecule under normal conditions, measures have to be taken to make it reactive. The environment has to be alkalic, and a temperature above 90°C is needed. Oxidized white liquor or pure $NaOH$ is added to raise the pH level to 10.5-11 while steam is added to control the temperature.

The first reaction tower is smaller than the second and has a higher pressure as well as a higher pH. Operating conditions for the two towers are shown in Table 1.1. Oxygen and steam are added between the towers to compensate for the reacted oxygen. After the reactors, the pulp is washed in two parallel washers where the freed lignin is removed. The pH is also lowered in these washers with filtrate from downstream processes.

Table 1.1: *Operating conditions in the two delignification reactors*

	Reactor 1	Reactor 2
Temperature [C]	90	95
Pressure [kPa]	650	300
Retention time [min]	30	90

The last stage is the pressurized hydrogen peroxide stage (PO) where the bleaching occurs. The conditions in this stage are similar to those in the O-stage and some lignin is removed in these reactors as well. However this is a secondary effect while the main goal is to bleach the pulp with H_2O_2. H_2O_2 reacts with OH^- to form HOO^- and water. HOO^- is the active chemical that bleaches the pulp. The effectiveness of this reaction is increased with increasing temperature. The pH level is also an important factor since HOO^- is more effective at alkaline conditions. However, a higher pH increases the decomposition of H_2O_2 into other molecules than HOO^-, which decreases the effectiveness of the process. The best results are achieved when pH is kept around 11 [11].

The setup of the PO stage is similar to the O stage and the operating conditions for the two reactors are shown in Table 1.2. $NaOH$, H_2O_2, O_2 and steam are added before the first reactor. Oxygen is added to pressurize the system and steam is added to raise the temperature. The same chemicals are added between the reactors to compensate for losses in the first reactor. The pulp is washed after the reactors in order to remove the final chemicals and excess lignin.

Table 1.2: *Operating conditions for the two hydrogen peroxide reactors*

	Reactor 1	Reactor 2
Temperature [C]	88	98
Pressure [kPa]	630	300
Retention Time [min]	30	180

The decomposition of H_2O_2 into undesired molecules is accelerated by transition metal ions left in the mass. It is therefore preferable to remove these metal ions before the PO-stage. An intermediate stage between the O-stage and PO-stage is thus needed, which is called the chelating stage (Q). The Q-stage consists of one tank and one reactor. The tank acts mainly as a buffer even though some reactions occur there. The main acting chemical in this stage is Ethylenediaminetetraacetic acid (EDTA). EDTA binds to metal ions and forms larger complexes which are then removed in the washing stages following the reactors. The effectiveness of EDTA is increased with lower pH however with diminishing returns. However, at low pH, a lot of the magnesium in the mass bound to the EDTA and is removed. Magnesium helps the pulp retain its strength during the reactions with oxygen and H_2O_2. The pH is therefore kept at pH 4-5 to balance the cost versus effectiveness and to prevent that magnesium is removed [12]. H_2SO_4 is added to control the pH level.

In order to reduce the amount of added chemicals in the three stages, the pH in the different processes are also regulated by exchanging filtrate between the stages since they have different pH. This is done in the washers after each stage. There are also several intermediate tanks in the process where the level controllers are suspected to behave poorly at the moment.

The bleaching plant is supervised by four separate MPCs, which at the moment are performing inadequately. The first regulates the delignification stage. The second controls the reactor in the chelating stage. The third and fourth MPCs control

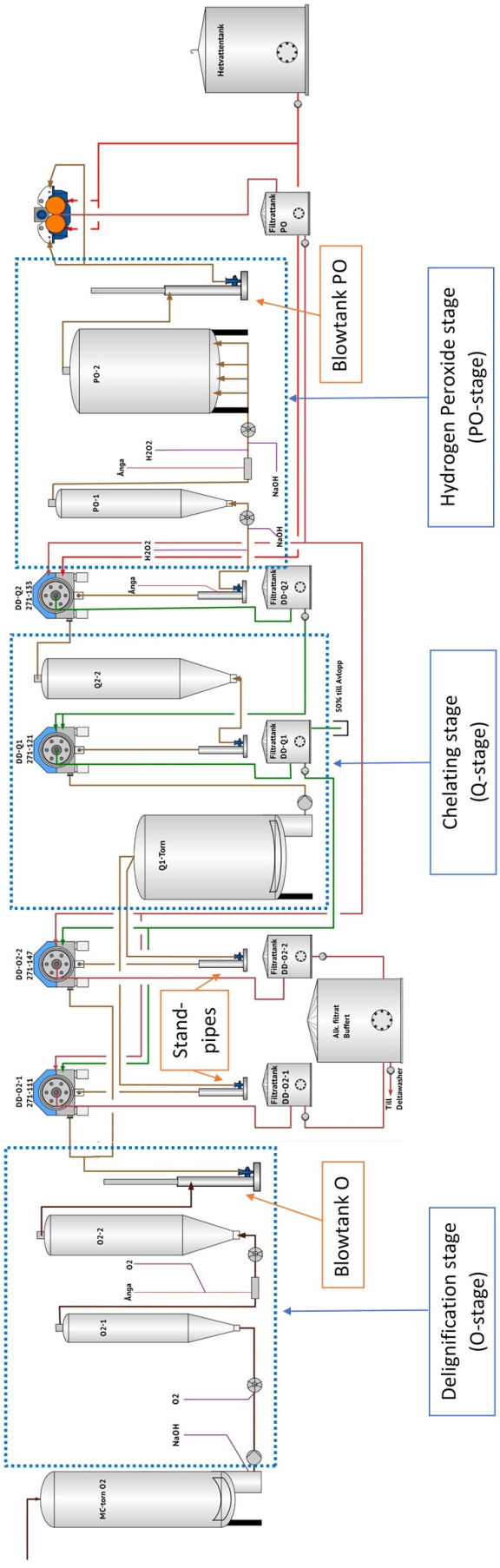


Figure 1.1: *A schematic view of the bleaching plant.*

the first and second rector in the peroxide stage, respectively. Each MPC has a set of *manipulated variables* (MVs), *disturbance variables* (DVs) and *controlled variables* (CVs). The manipulated variables are what the MPC changes to keep the controlled variable within its bounds. Disturbance variables are uncontrolled measured variables that are used to predict the optimum input. The variables relevant to each MPC are presented in Table 1.3. The models in an MPC describe the relationships between MVs and CVs as well as the relationships between DVs and CVs.

Table 1.3: *List of relevant parameters for the four different MPCs. O denotes the delignification step and consists of reactors O1 and O2. Q denotes the chelating step and consists of tower Q1 and reactor Q2. PO denotes the hydrogen peroxide step and consists of reactors PO1 and PO2*

Controlled Variables	Manipulated Variables	Disturbance Variables
MPC O		
• pH downstream of O2 • Kappa downstream of O2	• $NaOH$ addition before O1 • O_2 addition before O1 • Temperature before O2 regulated with steam	• Concentration of mass upstream of O1 • Kappa upstream of O1
MPC Q2		
• pH downstream of Q2	• H_2SO_4 addition before Q2	• pH upstream of Q2
MPC PO1		
• pH downstream of PO1 • Residues of peroxide downstream of PO1	• $NaOH$ addition before PO1 • H_2O_2 addition before PO1	• Brightness upstream of PO1
MPC PO2		
• pH downstream of PO2 • Residues of peroxide downstream of PO2 • Final brightness level	• $NaOH$ addition before PO2 • H_2O_2 addition before PO2	• H_2O_2 amount upstream of PO2 • pH upstream of PO2

1.2 Aims

The main goal of this thesis is to suggest improvements for the bleaching plant at BillerudKorsnäs's pulp and paper mill in Frövi. More specifically aspects that are investigated are

- Evaluation of sub-controllers for valves relevant for the MPCs.
- Suggestions for new models to the MPC that regulates the delignification stage. (MPC O)
- Evaluation of level controllers of intermediate tanks in the bleaching plant and suggest changes.

2 Theory

Modeling of chemical processes is in general a difficult procedure [13] and the bleaching step in a pulp mill is no exception [8]. There are two general ways of constructing the model. Either by first principles in the form of material and energy balances. Leading to a set of differential equations describing the system, or by black-box modelling, where empirical data is used to generate the model. The flexibility of the first principle models is in general better than that of empirical ones. However, they are often more expensive and time consuming to develop when large and complex system are to be modeled [13]. Black-box models on the other hand usually have better accuracy as long as the operation is performed within the region where the model has been generated. The process of developing the model is in general also faster. In this thesis, the focus will be on black-box models, which are further explained in the following sections

2.1 System Identification

Constructing appropriate black box models from time series data is called system identifiaction. The data required consists of inputs, and outputs that are generated by the system. The theory behind the system identification and the equations presented in this section are based on an article by Lennart Ljung [14].

The input at time t is denoted as $u(t)$ while the output is denoted $y(t)$. The relationship between them, i.e. the model of the system, is assumed to be described by the linear difference equation

$$y(t) + a_1 y(t-1) + \ldots + a_n y(t-n) = b_1 u(t-1) + \ldots b_n u(t-n). \tag{2.1}$$

Equation (2.1) can be rewritten so that the next value depends on all earlier observations, including both inputs and outputs, according to

$$y(t) = -a_1 y(t-1) - \ldots - a_n y(t-n) + b_1 u(t-1) + \ldots b_n u(t-n). \tag{2.2}$$

The following variables θ and φ are introduced to simplify the expression:

$$\begin{aligned} \theta &= \Big[a_1, \ldots, a_n, b_1, \ldots, b_n\Big]^T \\ \varphi(t) &= \Big[-y(t-1), \ldots, -y(t-n), u(t-1), \ldots, u(t-n)\Big] \end{aligned} \tag{2.3}$$

The expression (2.2) can then be rewritten into the more compact form

$$y(t) = \varphi^T(t)\theta. \tag{2.4}$$

Now, let $\hat{y}$ be an estimate of the output dependent on θ. The notation is

$$\hat{y}(t|\theta) = \varphi^T(t)\theta. \tag{2.5}$$

The goal of the system identification is to find a θ that minimizes the error between the estimated and measured output. This is done by using all measured inputs and outputs from preceding time instants, $t = 1$ to $t = N$. By introducing

$$Z^N = \{u(1), y(1), \ldots, u(N), y(N)\} \tag{2.6}$$

the task that minimizes the error becomes

$$\min_{\theta} V_N(\theta, Z^N), \tag{2.7}$$

where

$$\begin{aligned} V_N(\theta, Z^N) &= \frac{1}{N}\sum_{t=1}^{N}\Big(y(t) - \hat{y}(t|\theta)\Big)^2 \\ &= \frac{1}{N}\sum_{t=1}^{N}\Big(y(t) - \varphi^T(t)\theta\Big)^2. \end{aligned} \tag{2.8}$$

The θ that minimizes the so-called cost function is obtained by

$$\hat{\theta}_N = \arg\min_{\theta} V_N(\theta, Z^N). \tag{2.9}$$

The quadratic properties of the cost function V_N means that it is easy to find the minimum value. This is done by finding the derivative with regards to θ and set it to zero, i.e.

$$\frac{d}{d\theta}V_N(\theta, Z^N) = \frac{2}{N}\sum_{t=1}^{N}\varphi(t)(y(t) - \varphi(t)^T\theta) = 0. \tag{2.10}$$

Reordering gives

$$\sum_{t=1}^{N}\varphi(t)y(t) = \sum_{t=1}^{N}\varphi(t)\varphi^T(t)\theta, \tag{2.11}$$

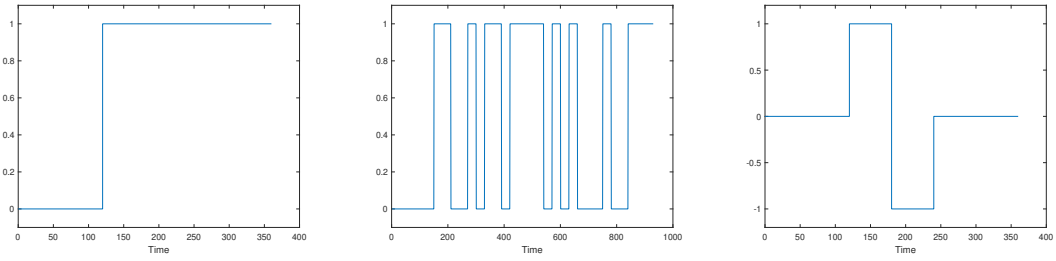
from which $\hat{\theta}_N$ can be expressed as

$$\hat{\theta}_N = \left[\sum_{t=1}^{N}\varphi(t)\varphi^T(t)\right]^{-1}\sum_{t=1}^{N}\varphi(t)y(t). \tag{2.12}$$

Numerical software tools can be used to solve equation (2.12). Matlab's System Identification Toolbox have been used to do so in this thesis.

2.2 Input signals to generate system data

Good models can only be generated if the available data is of good quality [15]. It is therefore important to use an input signal that excites the system and generates output data that describes its dynamics. However, the input signals have to be plant friendly, meaning that both inputs and outputs have to abide pre-determined user constraints [16]. The input signal can be designed in several different ways. Examples of three different input signals are displayed in Figure 2.1. The first example in the figure is called a step which is a very simple input. This can often generate a decent model which gives a rough estimate of the system's dominant time constant and system gain [15]. To generate a model that accurately describes the faster dynamics of the system is generally more complicated. An input signal that often is used in process industry to get a more accurate model of the system is the Pseudo Random Binary Signal (PRBS), which is explained further in the next section. These signals mimic the properties of white noise but are more plant friendly since the amplitude of the signals are bounded [16]. Another input signal that can be used is the Double Rectangular Pulse (DRP) which is essentially three steps performed in a series. The second step is larger and is performed in the reverse direction compared to the first step. This means that the value after the second step is lower (if the first step is positive) or higher (if the first step is negative) than the starting value. The third, and last, step brings the value back to its original value [17]. This input covers more of the system dynamics compared to the single step but performs worse than the PRBS. In addition to the mentioned inputs, there are other methods to create the input data, such as the sinusoidal input [16], but these are not used in this thesis.



(a) *Step input* **(b)** *PRBS input* **(c)** *DRP input*

Figure 2.1: *Examples of three different input signals used for identification.*

2.2.1 PRBS

The input signal PRBS shifts between two values at discrete time points with a predetermined highest frequency. The shortest allowed time between shifts is called the switching time, T_{sw}. The value of the signal may thus only change at these discrete time instant. However, the signal does not always change at each allowed time instant, meaning that the signal becomes irregular. This feature results in that most of the dynamics of the system can be captured. The time between each shift is kT_{sw}, where $k = 1, 2, ..., n$ denotes the number of time points passed before the shift occurs. The period of a PRBS signal is $N_{cyc}T_{sw}$, where N_{cyc} is the total amount

of passed time points. Both N_{cyc} and T_{sw} have to be predetermined to generate a PRBS signal [18]. It is suggested that these parameters should satisfy

$$T_{sw} \leq \frac{2.8\tau_{dom}^{L}}{\alpha}, \qquad N_{cyc} = 2^{n_r} - 1 \geq \frac{2\pi\beta\tau_{dom}^{H}}{T_{sw}}, \tag{2.13}$$

where τ_{dom}^{L} and τ_{dom}^{H} represent the dominant time constant range of the system and n_r is an integer greater than 1. The factors α and β represent the system and are often set to $\alpha = 2$ and $\beta = 3$ [18].

2.3 Modeling and PI tuning of tanks

For the purpose of level control tanks in process industry can in general be modeled as an integrator plus dead time (IPDT) system. These systems are not self-regulatory which means that the system will not stabilize if a change occurs [19]. The tanks that are modeled in this thesis are controlled by a valve at the bottom while the inlet acts as a disturbance. If the disturbance is constant while a small change is applied at the bottom valve, the tank will either empty or overfill. The model of an IPDT system is given by

$$G = \frac{k'}{s}e^{t_d s}. \tag{2.14}$$

By performing an open-loop step test, the slopes before and after the step can be compared in order to estimate k'. To do so, the valve is first placed in a position such that the level is either increasing or decreasing, and then, after a while, the position of the valve is changed such that the level changes in the opposite direction. The model gain k' is finally calculated using the slopes and differences in input according to

$$k' = \frac{slope_2 - slope_1}{OP_2 - OP_1}, \tag{2.15}$$

where OP is the operating point of the valve. The dead time can be determined by comparing the time instant at which the input is changed and the when response is observed [19].

PI controller settings for an integrating process can be determined by several methods. In this thesis, the SIMC method was selected [20]. The recommended parameters for tight control in the SIMC method is

$$K_c = \frac{0.5}{k'}\frac{1}{t_d}, \qquad T_I = 8t_d \tag{2.16}$$

where t_d is the observed dead time the PI-controller is on the form

$$C(s) = K_c\left(1 + \frac{1}{T_I s}\right). \tag{2.17}$$

The recommended parameters for smooth control is

$$K_c \geq K_{c,min} = \frac{\Delta q_0}{\Delta h_{max}}, \qquad T_I = \frac{4}{K_c k'}, \tag{2.18}$$

where the relation $\frac{\Delta q_0}{\Delta h_{max}}$ is the requirement of keeping the level within a range Δh_{max} when the flow is changing by Δq_0 [21].

3 Method

Three separate analyses have been performed within the scope of this thesis. Firstly, in order to evaluate the subcontrollers for relevant valves, a comparison between setpoint and output values has been performed. Secondly, to model the delignification stage and evaluate the proposed models, three trials with different input signals have been conducted. The input and output data generated by these trials were used to identify models with the help of the System Identification Toolbox in Matlab. Finally, to evaluate the level controllers, step tests have been performed to generate models from which optimal PI parameters could be calculated. The methods for each of these three analyses are presented in separate sections below.

3.1 Evaluation of subcontrollers for valves relevant for the MPCs

A supervisory controller will not perform better than the subcontrollers that regulates the variables used by the supervisory controller. The first step to improve the control of the plant is therefor to check if these control loops behave satisfactorily. To perform this analysis, *setpoints* (SP) and *process value* (PV) data were gathered from the processes considered. The information was gathered during four hours of normal operation. The SP and PV values were compared using the *root-mean-square* (RMS) method

$$RMS = \sqrt{\frac{\sum_{t=1}^{T}(y_r - y_t)^2}{T}}, \tag{3.1}$$

where y_r represents the SP and y_t represents the PV. T in the denominator was set to 1 since this number would be the same for all systems. Data was collected every ten seconds during four hours of normal operation. To make it easier to compare the different systems, all values were normalized by dividing each value with the corresponding maximum values for the PV. Cases with a high error were then further investigated.

3.2 Model estimation for the delignification stage

The three trials on the delignification stage were supposed to be performed during normal operation when the plant was run at maximum capacity. A criteria for the trials was that they had to be plant friendly, i.e. they were not allowed to disturb the bleaching process too much. In order to ensure this, the trials were designed in cooperation with a responsible operator who decided the maximum and minimum values that were allowed for each trial. Furthermore, the tests had to be designed such that it was possible for one person to conduct the entire experiment, resulting in a time limit of 16 hours per trial. Experience from the first trial was used as a base for the design of the second and third trial.

The first trial used three uncorrelated PRBS signals as inputs for three valves. These valves regulated the flow of $NaOH$, O_2 and steam. The plan for the inputs in the

first trial is presented in Figure 3.1. In order to estimate T_{sw} according to Equation (2.13), time constants from old models had to be used. These models suggested that the three relevant time constants all were around 30 min. An optimal choice for T_c would thus have been be a number lower than 30 min. However this was prevented by the slow sampling of Kappa and T_c was therefore chosen to be 30 min. The decision was thus based more on limitations than on theoretical optima. Given the time limit for the trial, N_{cyc} was chosen as 31 to create a test that lasted 15.5 hours. The trial could have been divided into three parts where the system was excited by one input at a time while the other inputs were kept constant throughout the entire test. However due to time constraints, it was decided to perform the three parts simultaneously.

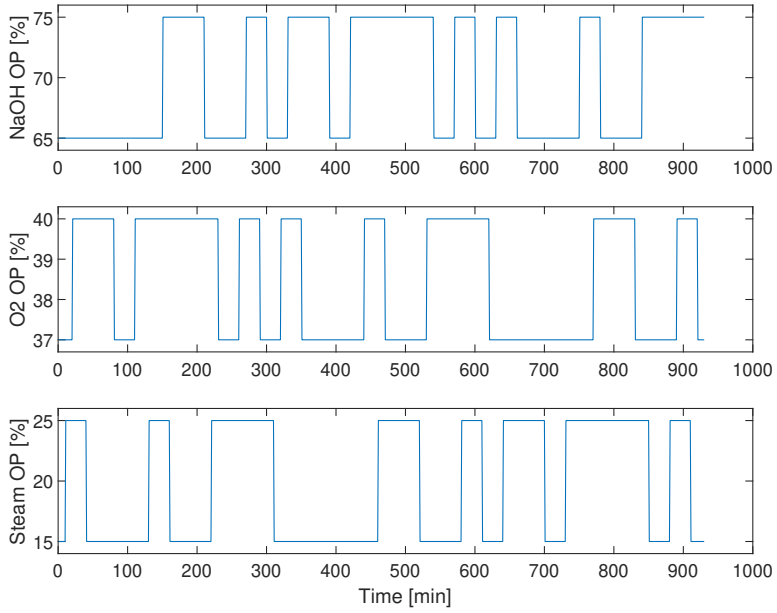


Figure 3.1: *Input schedule for relevant valves in the first trial. OP denotes the operating point and corresponds to the opening of the valve measured in percent.*

The method for the second trial was altered from the first trial, which can be seen in the plan for the second trial presented in Figure 3.2. The minimum time between changes in the inputs had to be longer than the time that was used in the first trial in order to model Kappa. Apart from adjusting this, it was also decided that only one input at a time should be changed in the second trial. A DRP signal was used in this trial to reduce the total time of the experiment. The time between pulses for the different inputs was set to 1 hour with the hope that this would be long enough to model Kappa. The first change in input occurred after three hours to ensure that the system had reached a steady state before it was manipulated. This was based on the time constant which was 30min, and the dead time which was estimated to be approximately two hours. In order to ensure that the different input signals did not interfere with one another, a delay of 3 hours was added before changing from one input to another. The trial could in practise have been performed as three separate

tests.

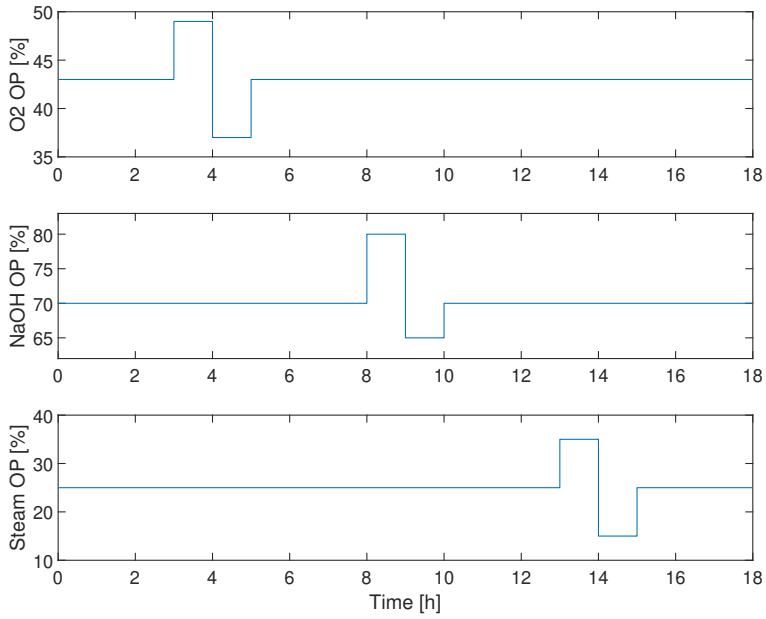


Figure 3.2: *Input schedule for relevant valves in the second trial. OP denotes the operating point and corresponds to the opening of the valve measured in percent.*

The third trial was conducted in a similar manner as the second trial. The plan for this trial is shown in Figure 3.3. The reason for conducting this trial was that the results from the second trial were unsatisfactory. The time before the first step, as well as the time between changes of inputs was reduced to 2.5 hours because of a higher production rate. The input signal for $NaOH$ was identical to the one used in the second trial apart from an increase of 5 units in the starting position. The temperature test (steam) was however changed completely. The first and second trials were performed in open-loop while in the third trial, the temperature controller was activated, resulting in a closed-loop setting. The setpoint for the inlet temperature was changed instead of changing the steam valve directly. This was done because of safety reasons as it was noticed in the first trial that the temperature could increase rapidly.

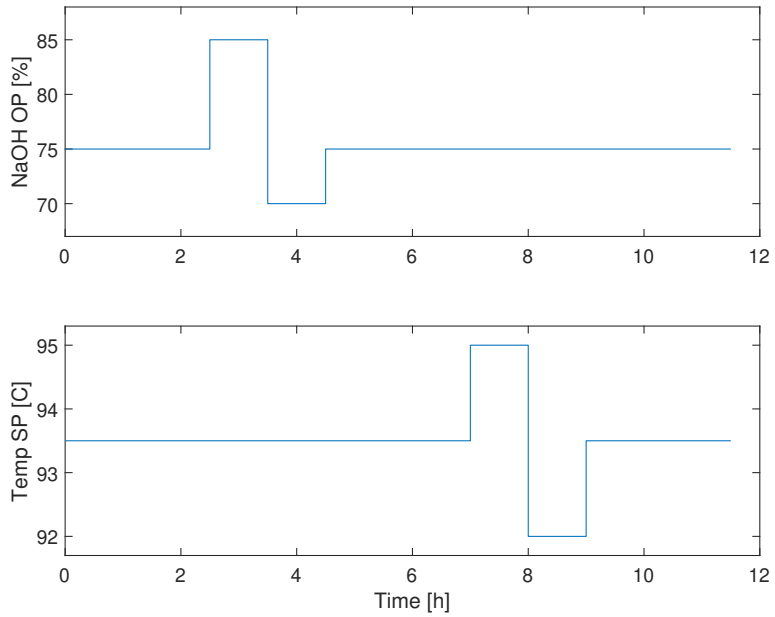


Figure 3.3: *Input schedule for relevant valves in the third trial. OP denotes the operating point and corresponds to the opening of the valve measured in percent. SP denotes the setpoint of the subcontroller.*

3.2.1 System identification

The data gathered from the trials were used in the System Identification Toolbox app in Matlab. Firstly, the means were removed. Secondly, the data was divided into estimation and validation data. Finally, the data was used to estimate models. Only first order process models were created on the form

$$G = \frac{K_p}{1 + T_p s} e^{-T_d s}. \tag{3.2}$$

3.2.2 Comparison between new and old models

The models that currently are used in the MPC are based on relations from input setpoints to controlled variables while the models generated in this thesis mainly are based on the realtions from operating points to controlled variables. The difference is caused by the open-loop testing that is used when estimating most of the new models. In order to compare the new models with the old, and to eventually be able to add the new ones to the MPC, the closed-loop system of the valves must be added. The transformation from the open-loop format to closed-loop is given by

$$G_{closed} = \frac{C}{1 + CP} G_{open}, \tag{3.3}$$

where C denotes the controller and P denotes the model of the corresponding valve. In addition to this transformation, the units of the flow in the new models have to

be changed in order to be comparable with the units in the old models. The unit of the setpoints for flow of incoming chemicals for the current models of the MPCs is $kg_{chemical}/ton_{production}$, while the model (3.3) is based on either l/s or g/s. This means that the new models have to be multiplied by a constant before they are compared to old models.

3.3 Evaluation of level control in intermediate tanks

Four tanks were of interest when creating models for the intermediate tanks; the O blowtank, the PO blowtank and the two standpipes before Q1.

The blowtanks are used to remove the excess O_2 after the second O-reactor. The blowtank O also acts as a buffer between the O- and Q-stages. In the standpipes, the chemicals that are used in the Q-stage are added.

The step tests on the blowtanks were performed when the controller was turned off. The initial steps were small in order to identify where the switch occurred from filling to emptying of the tank. When this point was identified, the steps were increased in size until a clear slope could be noticed in the output. The models were created based on the final step. However, in the case of the PO blowtank, the three final steps were used for identification.

No tests were performed on the standpipes. The concern was that it might empty or overflow due to the small size of the pipes as well as the high incoming flow. The section of the pipe that is measured by the instrument is only $1m^3$ and the incoming flow is above $20l/s$. However, data from older experiments was found which could be used to create models for the standpipes.

The optimal PI parameters were calculated from Equations (2.16) and (2.18).

4 Results

The results obtained from evaluating the subcontrollers, generating models of the delignification stage and PI tuning of level controller are presented in the section below.

4.1 Evaluation of subcontrollers for valves relevant for the MPCs

The observed error from comparing PV and SP values for various valves and their corresponding controllers are presented in Table 4.1.

Table 4.1: *Deviations from setpoint at various valves expressed in normalized RMS and total accumulated error (not normalized). The mean value is the average of the PV. The top part of the table includes current relevant parameters for the MPCs while the bottom part includes other relevant valves for the process*

Valve	Norm RMS	Accumulated Error	Mean value
White liquor O1	0.062	1.87	0.43
O_2 O1	2.53	1765	17.2
Temp O2	0.11	309.2	92.98
H_2SO_4 Q2	5.02	2.09	0.01
H_2O_2 PO1	0.023	0.98	0.20
NaOH PO1	0.16	4.42	0.34
H_2O_2 PO2	2.56	1.39	0.01
NaOH PO2	0.012	0.68	0.19
O_2 O2	0.17	44.56	8.47
Massflow O1	0.27	259.8	30.8
H_2SO_4 Q1a	1.69	4.63	0.07
H_2SO_4 Q1b	1.14	3.48	0.08
$MgSO_4$ Q2	0.37	0.91	0.07
EDTA Q1a	0.30	0.30	0.033
EDTA Q1b	0.46	0.52	0.037
EDTA Q2	0.31	0.13	0.015
O_2 PO1	0.09	33.62	12.5
$MgSO_4$ PO1	0.37	0.91	0.07
O_2 PO2	0.11	43.1	12.5

It can be noted that three of the valves included in the MPCs have high RMS and thus deviate substantially from their setpoints. These are; oxygen before the first O reactor, sulfuric acid before the Q reactor and hydrogen peroxide before the second PO reactor. However the mean values for the H_2SO_4 and H_2O_2 valves are very low (0.01 liter/s) and when inspected further the PVs were found to follow the SPs fairly well. A similar inspection of the oxygen valve however showed poor results at certain production levels, as explained further in the following section.

From the table it can also be noted that the two valves that add H_2SO_4 before the Q tower have a significant RMS, but since they are not relevant for the MPCs, they have not been investigated further.

4.1.1 O_2 valve before O1

The comparison of SP and PV values for the O_2 valve before O1 in Figure 4.1 shows that the valve is behaving differently at different levels of production. Higher production level means that the flow of oxygen has to be higher. The PV is heavily oscillating at the lower level while the error is considerably smaller at a higher level.

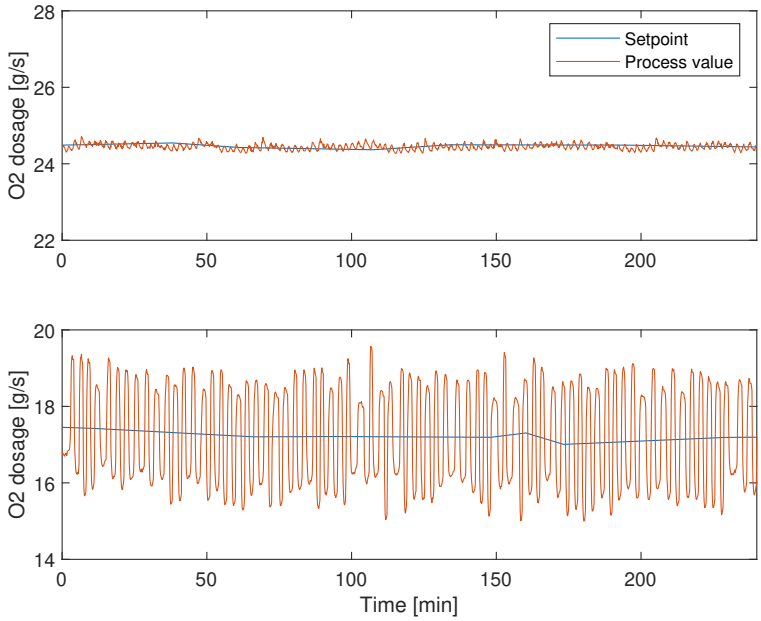


Figure 4.1: *The difference between SP and PV for the O_2 valve. The top figure shows the difference when the flow is ca 25g/s while the lower shows the difference when the flow is ca 17g/s*

An open-loop test consisting of a sequence of steps were performed to analyze the behavior of the valve. The steps were performed in a region where the oscillation was expected to increase. Figure 4.2 shows the input used to conduct the test as well as the corresponding open-loop response.

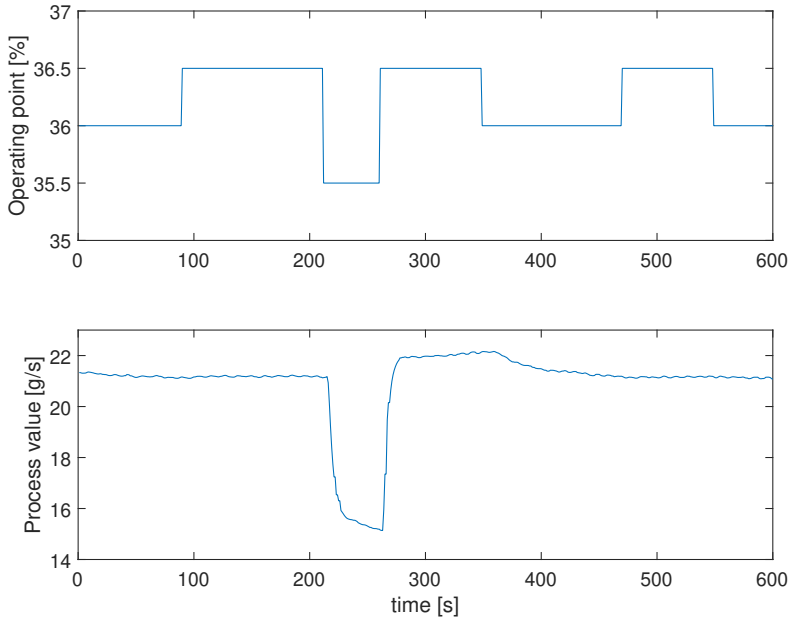


Figure 4.2: *A series of steps performed in open loop on the first O_2 valve. Note the large change in PV occurs at the same time as the OP is changed from 36.5 to 35.5.*

When comparing the plots it is seen that the valve is not operating linearly and that the shift is occurring at an OP somewhere between 35.5% and 36%. Since this problem occurs at a certain region it is possible that it is caused by stiction. Stiction implies that a valve's smooth motion instead consists of a static period with no motion followed by a jump [22]. This is probably caused by wear of the valve since it has not been changed for more than 20 years. It is thus recommended that the valve is either repaired or changed.

4.2 Model estimation for the delignification stage

The results of the three trials performed on the O-stage is presented in separate sections below.

4.2.1 First trial

Originally, the test was intended to be longer but an unfortunate stop occurred at a section downstream of the O reactors and the plan thus had to be modified. The test was not restarted and as a result only the later part of the original plan was carried out. It was initially intended to have a production rate of 19 ton/h but this was also affected by the stop. Instead the production rate was 17 ton/h.

Before models could be estimated from the data, the actual values of the chemical flows and temperature had to be checked. The reason for this is that the valve for O_2 addition function poorly. Figure 4.3 shows input values for the valve positions and the different flows and temperature.

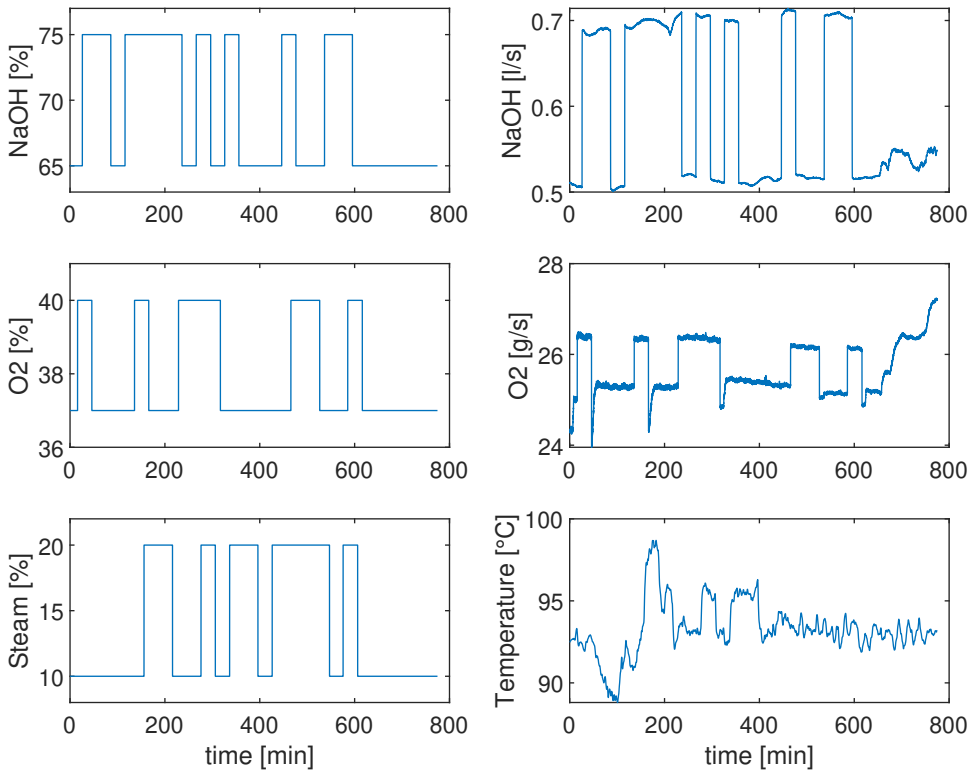


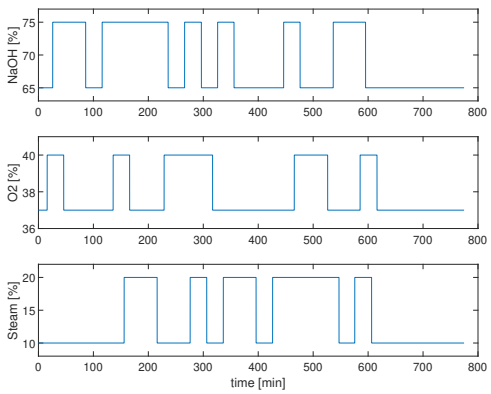
Figure 4.3: *Comparison between OP values and measured PV values for the inputs. OP are on the left and their respective PV are on the right.*

The rise in flow at the end of the plots is due to that the supervisory controller had to be turned on earlier than intended. The production had to be increased and since the test had to be conducted at constant production rate, the test ended earlier

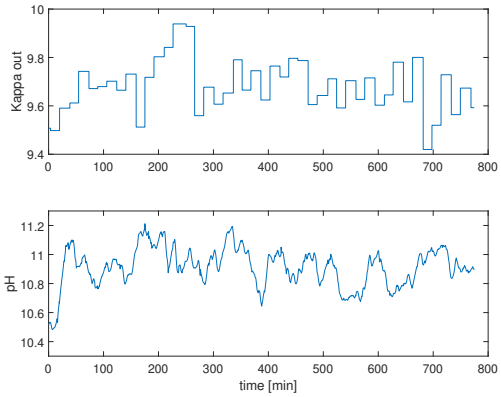
than planned. The OP curves also followed this trend. However, those values were manipulated to be constant after the final step. This was done to make it easier in the identification stage. Since there is a large delay between inputs and outputs for the process, the observed increase at the end of these PVs will not affect the measured outputs. It is thus believed that this manipulation will not change the results.

It can be noted from Figure 4.3 that the valve for $NaOH$ is working as expected since the OP has a corresponding effect on the PV. However, the two other valves are not working perfectly. The oxygen valve exhibits significant undershoots. This can however be discarded due to the large time constants of the system. The problems with the temperature controller cannot be discarded though. A further discussion about this controller is presented in 5.2.

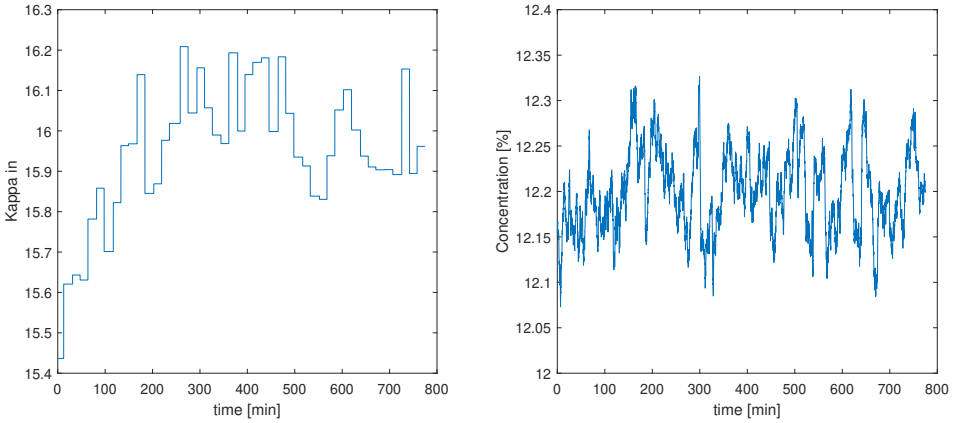
The main results of the first modified test are presented in Figure 4.4 and consists of inputs and outputs as well as measured disturbances.



(a) *Input signals.*



(b) *Output signals.*



(c) *Measured disturbances.*

Figure 4.4: *Data generated for the first trial.*

As expected it was not possible to generate models for the dependence between kappa and the inputs. The frequency of the sampling needs to be drastically increased to generate good models. The output kappa value are also heavily dependent on the incoming kappa number. Since this is not controllable, it is hard to generate a model. However, models of pH were created with the System Identification toolbox despite the problems with the data. The models were generated based on data from the first 400 minutes of the trial. The remaining data was used as validation data. Equations (4.1) and (4.2) show two candidate process models for the pH.

$$G_{NaOH,pH,1a} = \frac{0.021}{492s+1}e^{-7515s}, \qquad G_{Steam,pH,1a} = \frac{-0.018}{888s+1}e^{-5323s} \tag{4.1}$$

$$G_{NaOH,pH,1b} = \frac{0.021}{360s+1}e^{-7648s}, \qquad G_{Steam,pH,1b} = \frac{-0.013}{404s+1}e^{-5754s} \tag{4.2}$$

Figure 4.5 shows the simulated response of models (4.1) and (4.2) when the validation input signal is used. They are compared to the actual response of the system. The first part of the series cannot be used to determine the best model due to the long delays. It is hard to determine which model represents the real system most accurately. Model (4.2) matches the higher peaks better, but model (4.1) is generally better at predicting the low peaks. The problems with the temperature controller means that these results might be inaccurate. A second and third trial were therefor performed to decide if these results are valid.

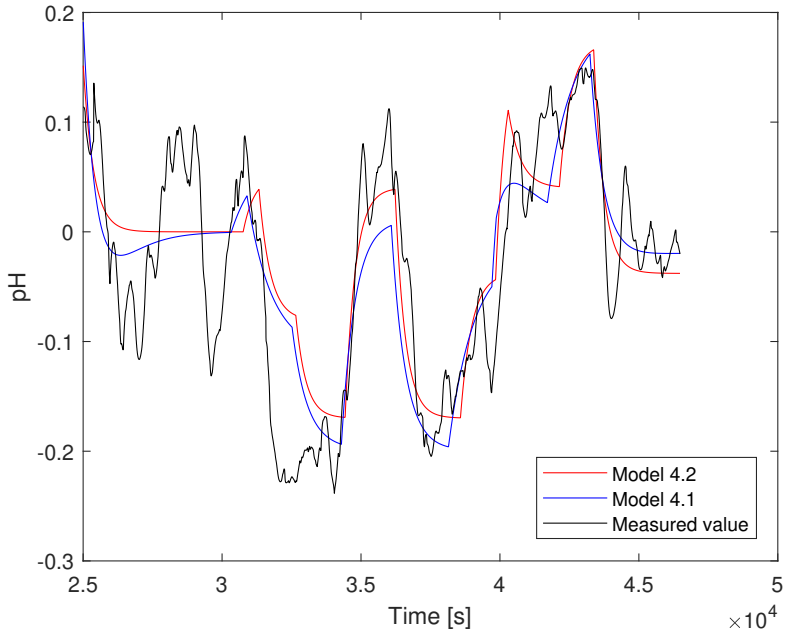
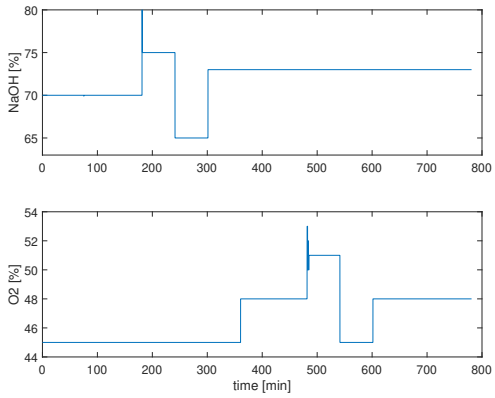


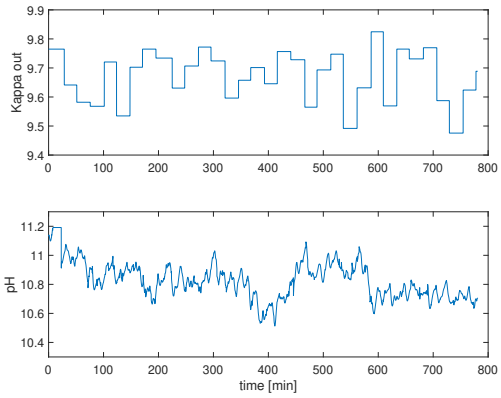
Figure 4.5: *Simulated responses of models* (4.1) *and* (4.2) *based on inputs of the first trial against validation data.*

4.2.2 Second trial

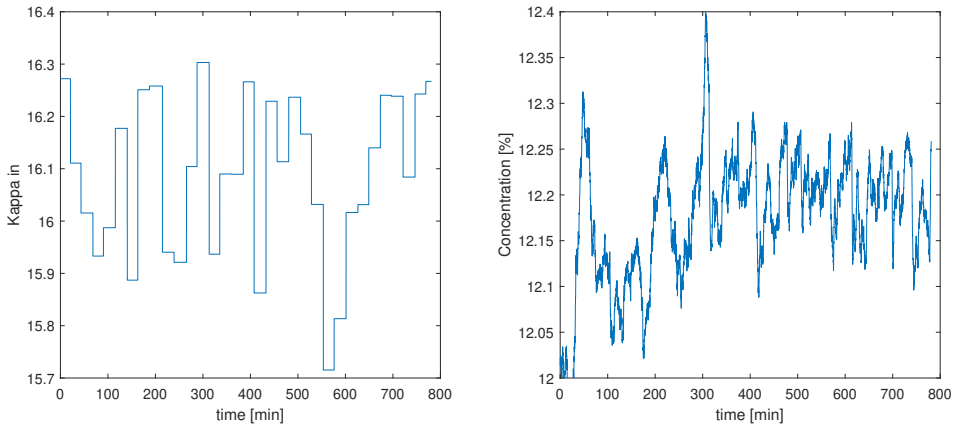
The second trial generated similar results as the first one. The results are presented in Figure 4.6 and consists of inputs and outputs as well as measured disturbances.



(a) *Input signals.*



(b) *Output signals*



(c) *Measured disturbance.*

Figure 4.6: *Data generated for the second trial.*

Kappa was impossible to model for this case as well even though the time between changes was increased compared to the first trial. The pH test generated better outputs than Kappa, but are still not very good. Due to communication problems with the operators during the trial, the production rate was changed without notice. This resulted in some changes from the intended plan which can be seen in Figure 4.6a. For example the final value of $NaOH$ is higher than the initial value, and the flow of O_2 had to be increased earlier than intended. The spikes in both $NaOH$ and O_2 after the first intended step are due to a higher flow of chemicals than expected. The valve openings were reduced directly after the initial step to compensate for this. The spikes were removed before identification. It is believed that, since the spikes are short and the time constants of the system is large, this will not have any effect on the results. The interesting region of the trial is enhanced in Figure 4.7.

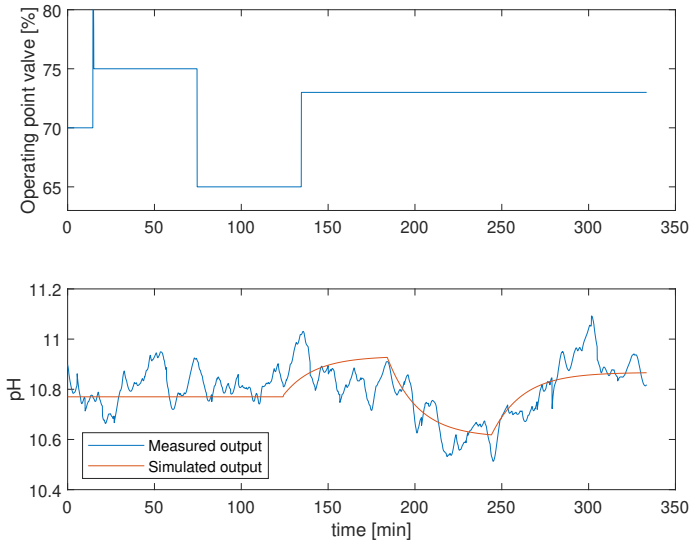


Figure 4.7: *Interesting part of trial 2 used as identification data. The measured output is plotted together with the simulated output from model* (4.3).

There is no clear response in the pH value from the first step while the second and third steps yield a noticeable response. Since the response is nonlinear, it will be hard to generate a good linear model from this trial. The best fitted model from this data is plotted together with model (4.1) against the measured values in Figure 4.8. The model (4.3) is seen to give a better match to the actual data compared to model (4.1).

$$G_{NaOH,pH,2} = \frac{0.0325}{1064s + 1} e^{-6570s} \tag{4.3}$$

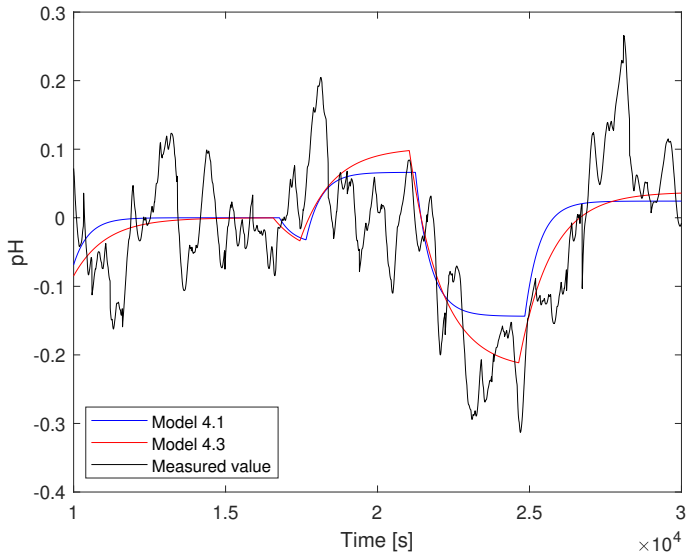
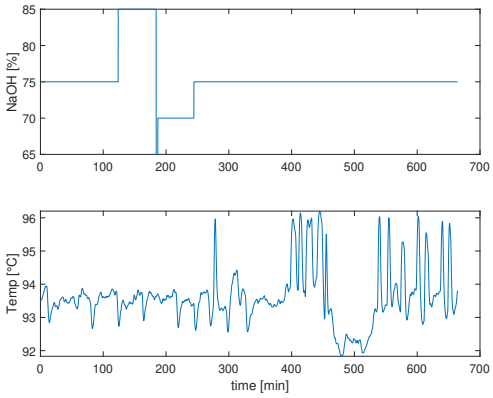


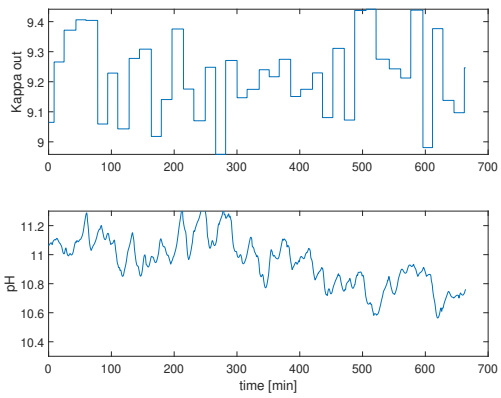
Figure 4.8: *Simulated response of models* (4.1) *and* (4.3) *based on inputs of the second trial against identification data.*

4.2.3 Third trial

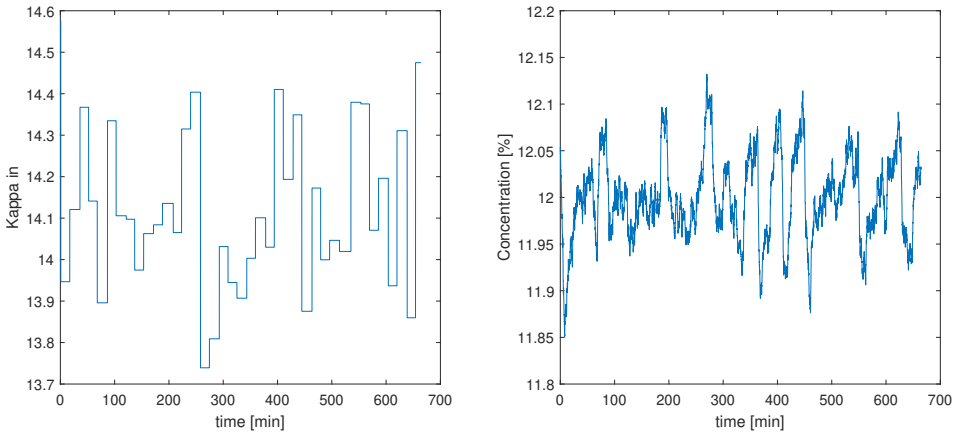
The third trial had similar problems as the other trials as can be seen in Figure 4.9 where the results are presented. These results consist of inputs and outputs as well as measured disturbances.



(a) *Input signals.*



(b) *Output signals.*



(c) *Measured disturbances*

Figure 4.9: *Data generated for the third trial. Note that the PV of the temperature controller is plotted instead of the SP.*

Models for Kappa could not be identified in this trial either, and the problems with the temperature controller are highly noticeable. The output data of pH seems to follow a decreasing trend. This is discussed further in section 5.4. No disruptions occurred during this trial. The interesting part of the trial regarding the $NaOH$ model is enhanced in Figure 4.10.

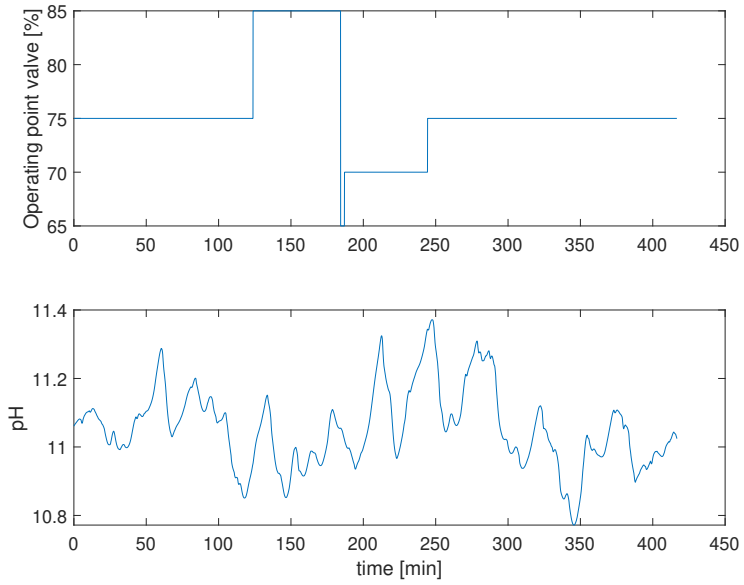


Figure 4.10: *Interesting part of trial 2 used as identification data.*

The data from the third trial is noisy but it is possible to distinguish a trend. The trend does however not match the output of the other trials. The best fitted model from this data is displayed in Equation (4.4). It is plotted together with model (4.1) against the measured values in Figure 4.11.

$$G_{NaOH,pH,3} = \frac{0.018}{218s + 1} e^{-6374s} \tag{4.4}$$

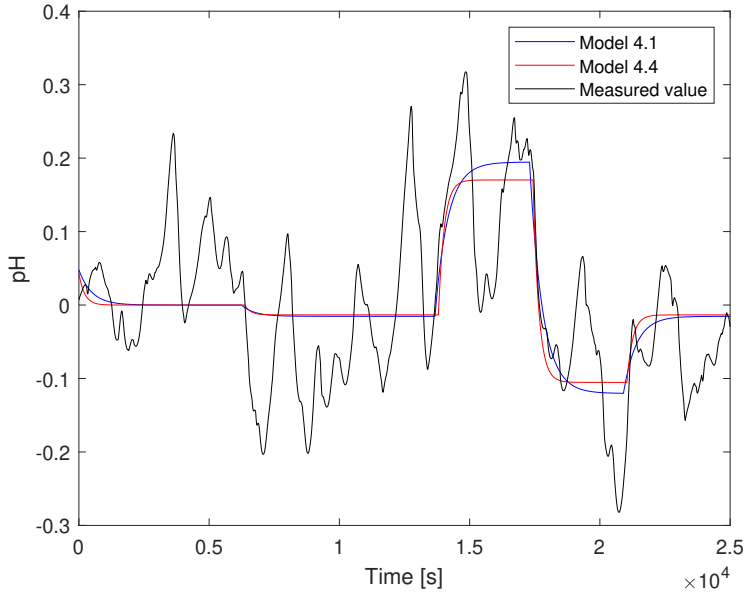


Figure 4.11: *Simulated response of models* (4.1) *and* (4.4) *based on inputs of the third trial against identification data.*

It is clear from Figure 4.11 that none of the models match the real data and that no conclusions can be drawn from this experiment.

Due to the many disruptions and uncertainties during the trials, it is not possible to properly evaluate all the estimated models and thus not possible to identify the best model. However the $NaOH$ part of model (4.1) appears to describe the system the most adequately. The transformation of this model from open-loop format to closed-loop given by (3.3) is

$$G_{NaOH,pH} = \frac{0.059}{1308s + 1} e^{-7500s} \tag{4.5}$$

Furthermore, no models could be estimated from the DVs to the CVs.

4.3 Evaluation of level control in intermediate tanks

The results from the tests performed on the intermediate tanks are presented in this section. The optimal PI values for each tank are also presented.

4.3.1 Blowtank after delignification stage

The input and the resulting output for the test performed on blowtank O is presented in Figure 4.12.

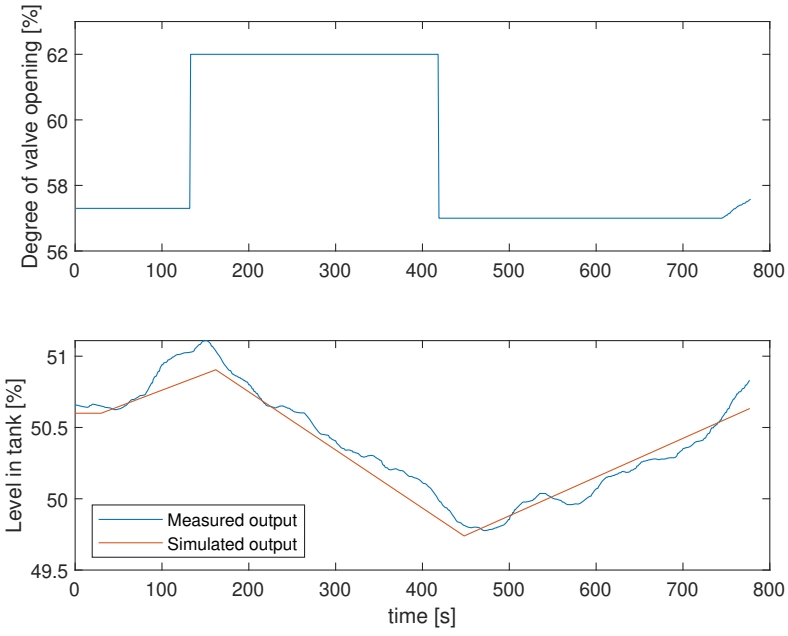


Figure 4.12: *Input (top) and output (bottom) from the step test performed on the blowtank O. The yellow line represent the simulated response from* (4.6).

The model for this tank is calculated using the data from the first negative slope and the second positive slope in Figure 4.12. Equation (4.6) is the transfer function that best matches the real data.

$$G_{valve,level,O} = \frac{-0.0014}{s} e^{-30s} \tag{4.6}$$

The optimal strict and optimal smooth controller settings are presented in Table 4.2.

Table 4.2: *Optimal strict and smooth K_c and T_i values for the level controller in blowtank O. The current values are also presented.*

	K_c	T_i
Strict	12.3	240
Smooth	1	2944
Current	2	1122

The current controller was desired to behave more smoothly and its settings were thus changed to better resemble the optimal smooth values. $K_c = 1$ and $T_i = 1500$ were chosen. A comparison between valve behavior before and after the changes are presented in Figure 4.13. From the plots it is seen that the behaviour of the valve is improved after the changes, since it fluctuates less.

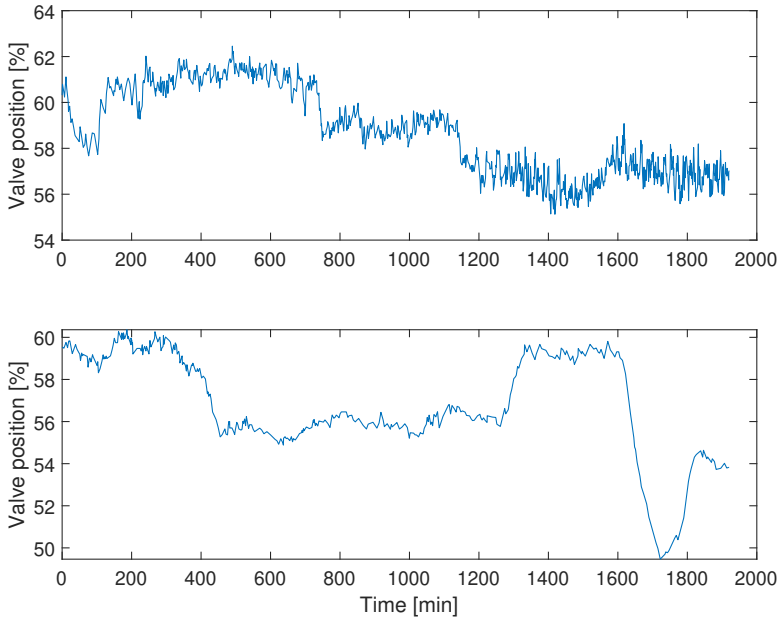


Figure 4.13: *Comparison between the behaviour of the valve before the changes (top) and after the changes (bottom).*

4.3.2 Blowtank after hydrogen peroxide stage

The results from the test on the blowtank after the PO stage is presented in Figure 4.14.

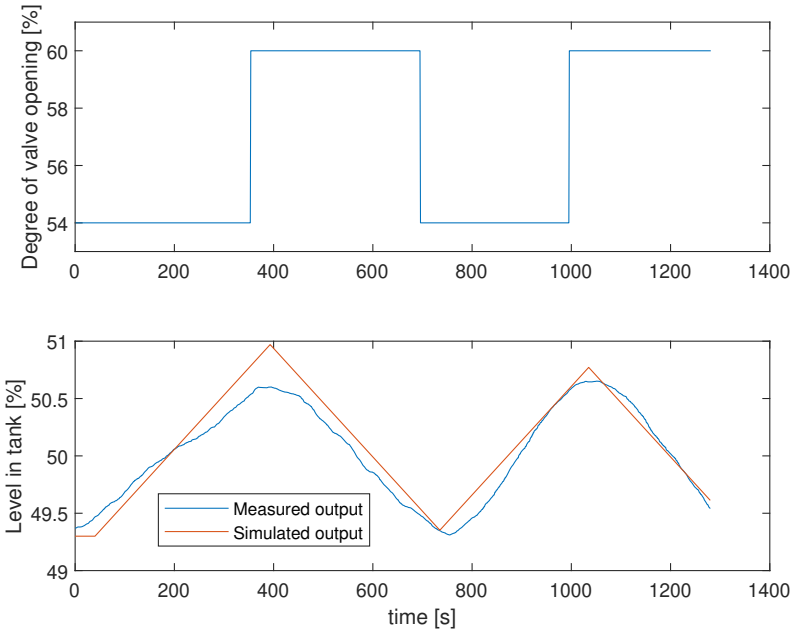


Figure 4.14: *Input (top) and output (bottom) from the step test performed on the blowtank PO. The yellow line represent the simulated response from* (4.7)

The model in (4.7) was calculated by using the average that was obtained from comparing all slopes in Figure 4.14.

$$G_{valve,level,PO} = \frac{-0.0016}{s} e^{-40s} \tag{4.7}$$

The optimal strict and smooth controller settings are presented in Table 4.3.

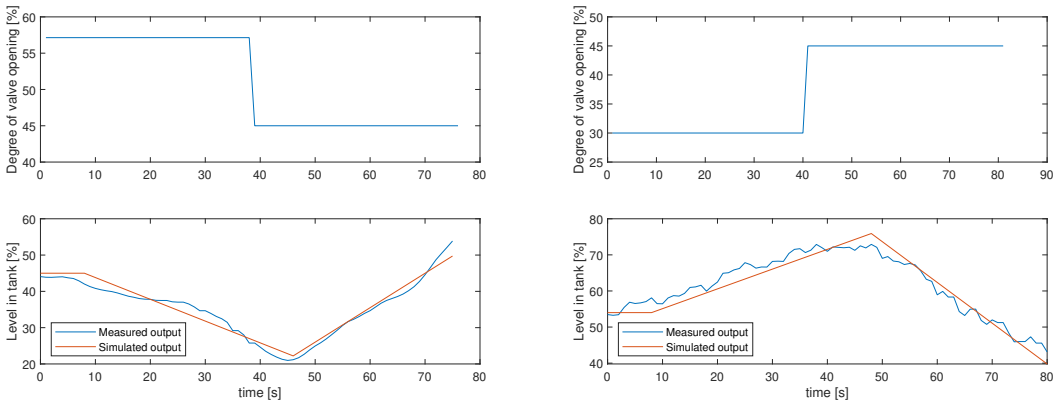
Table 4.3: *Optimal strict and smooth K_c and T_i values for the level controller in blowtank PO. The current values are also presented.*

	K_c	T_i
Strict	7.93	320
Smooth	1	2536
Current	1	1500

The current values of K_c and T_i are close to the optimal smooth values.

4.3.3 Standpipes before chelating stage

The data that was found from previously conducted experiments which was used for the identification of the standpipes is shown in Figure 4.15.



(a) *First standpipe.* **(b)** *Second standpipe.*

Figure 4.15: *Inputs (top) and outputs (bottom) from the step tests performed on the two standpipes. The yellow lines represent the simulated responses from* (4.8).

The models that best match the experimental data is

$$G_{valve,level,Pipe1} = \frac{-0.128}{s}e^{-8s}, \qquad G_{valve,level,Pipe2} = \frac{-0.112}{s}e^{-8s} \tag{4.8}$$

Optimal PI regulators for these models are displayed in Table 4.4,

Table 4.4: *Optimal strict and smooth K_c and T_i values for the level controllers in the two standpipes. The current values are also presented.*

First standpipe

	K_c	T_i
Strict	0.49	64
Smooth	0.25	125
Current	0.28	28

Second standpipe

	K_c	T_i
Strict	0.56	64
Smooth	0.25	143
Current	0.45	60

The current K_c and T_i parameters for the first standpipe is stricter than the optimal strict values, while the same parameters are close to the optimal strict values for the second standpipe.

5 Discussion

Modelling of bleaching reactors is in this thesis shown to be very difficult. One reason for this are the many sources of disturbances that will effect the experiments. The largest issues have been the slow sampling rate of Kappa and the inadequate temperature control. In addition, the quality of the tests was effected by the tight restrictions to access the operator room due to the current pandemic. This led to communication problems where, for example, the operator, without notice, lowered the production rate in the second trial. These complications have had a big impact on the results. However, modeling of the intermediate tanks was successful and new PI parameter values could be suggested.

5.1 Models of Kappa

The slow sampling of Kappa means that no models could be estimated for Kappa. This is unfortunate since Kappa is the parameter that identifies how well the reactor is performing. Improving the models for Kappa will lead to better control and the processes downstream would thus become more stable. This would also be the case if Kappa from upstream processes was more constant. It is possible that Kappa could be modelled if the sampling rate is increased. Currently however, this is not possible due to the amount of time that is required for the Kappa analyzer to work properly. As it is now, it might be possible to determine the gain of the corresponding transfer functions with a test that involves large steps performed over longer time periods. However this would greatly impact the bleaching process negatively, and it would probably not yield any model that describe the system sufficiently well.

5.2 Problems with control of temperature before O2

The temperature controller has a few problems since the temperature does not respond to changes in the amount of steam, and since the process values are seen to deviate from the setpoints. These problems were not discovered when the initial screening of sub controllers was performed since its normalized RMS value were low. Therefore, it was decided that it did not need further investigation at the time. Another observation is that the issues appeared both when the controller was active as well as when it was turned off, i.e. both in closed- and open-loop.

The problems in open-loop is likely due to pressure changes in the steam pipes before the valve. If other parts of the plant are using the steam, the pressure might drop and thus reduce the flow through the pipes. This will in turn reduce the temperature increase of the pulp. The temperature of the pulp from the first reactor will of course also effect the temperature before the second reactor. The pressure before the valve could be added to the control loop to better control the flow of steam.

For the case with closed-loop in the third trial, the temperature was seen to deviate greatly from its setpoint, which caused poor input data quality. The temperature seems to be oscillating around its setpoint when it is increased. This implies that

the controller might be too aggressive. However, these problems are not occurring to the same degree at lower temperatures. This controller should be looked over before another test is performed on the delignification stage.

Because of these issues, it is challenging to create a good model of how the pH depends on temperature and steam valve position. However, the models created from the first trail seem to match the real data fairly well. This indicates that the correlation between the actual temperature in the reactor and the positioning of the steam valve might be linear. This means that it could be possible to create a linear model describing the relation between steam valve and pH.

5.3 Best models of pH

If it is assumed that the temperature data is good enough for identification, it is still not clear from the tests which model most closely resembles the real system. Two models are obtained from the first trial that both match the real data quite well, but it appears that model (4.1) is a better match.

When the $NaOH$ part of this model is compared to the second trial, it does however not match the real data well. The results from this trial might, however, be inaccurate due to unexpected changes in production rate. For example, no clear response was seen from the first step. The reason for this could be that the changes in production rate occurred around the same time as this step. Model (4.3) from the second trial matches this dataset better than (4.1), but this is most likely due to the fact that this model was estimated based on this data.

Furthermore, model (4.1) does not match the data from the third trial either. Due to the long retention time inside the system there is a large delay between inputs and outputs. Thus the noted increase in pH which occurs directly after the first step cannot be caused by the step. This means that there is something wrong with the data from this trial. The problems with this data might be due to the downwards trend of the pH, where something is seen to disturb the process other than the performed test. Since both the second and third trial failed to produce a good model, the pH model from (4.1) has now been implemented in the MPC. However, the performance of this model will not be evaluated in this thesis due to time limitations.

5.4 pH trends and proposed changes to delignification MPC

The pH is seen to follow some kind of trend, and to see if a larger trend could be detected, data from one week of uninterrupted production was thus gathered. The plot of this data is presented in Appendix A. The pH value is seen to oscillate between 10.5 and 11 at a constant period. These are the accepted boundaries for the process, but this behaviour is not desirable since it can lead to uneven quality or unnecessary high dosage of chemicals. The oscillations is most likely due to the circulation of the filtrate. The solution which the pulp is suspended into is recirculated and used in the washing stage before the first delignification reactor. This implies that if the pH of the pulp leaving the second rector is high, the filtrate

returning to the beginning of the process will also have a higher pH value. Since the pulp is mixed with this filtrate in the beginning of the process, this circulation implies that a cycle of higher and lower pH values can be created.

To evaluate this, the conductivity of the filtrate was monitored during the same period as the data for the pH was gathered. This indicated how clean the filtrate was. A low conductivity imply cleaner water, while a high conductivity indicate that the filtrate is more contaminated by for example $NaOH$. A similar trend was found for the conductivity as for the pH, which further supports that the recirculation of filtrate is the main reason for the oscillation.

The current configuration of the MPC that regulates the delignification stage is not able to accurately predict future pH values. To only change the model will however not be sufficient, since there are several other factors that affect the pH. A proposed adjustment is to add the conductivity of the filtrate as a disturbance variable. This would hopefully help the MPC to predict future values more accurately. Another proposal that might improve the prediction is to add a dead time adaptive model. The current models have a fixed dead time even though this parameter is varying in reality. The actual dead time is based on production level and it can vary between 2 and 3 hours.

5.5 Level control of intermediate tanks

The goal of this investigation was to change the undesired behaviour of valves that fluctuate heavily for the four intermediate tanks. The aim is thus to adjust the controllers so that they resembles an optimal smooth controller according to SIMC rules. The PI parameters obtained from the tests imply that some changes could be advantageous for some of the tanks.

The optimal PI parameters generated for the O blowtank suggest that the parameters could be changed to smoothen the control. Implementing the new values for the PI parameters has greatly reduced the movement of the valve which will reduce the wear of the valve. This will also affect a pump located after the valve. This pump increases the pressure allowing the pulp to flow through the pipe. The setpoint for the pump is dependent on the positioning of the valve, and a smoother movement will thus decrease the changes in pump speed which in turn will decrease the wear of the pump. A higher value for the parameter T_i was also tested, but it appeared that disturbances were not handled well at these settings.

A similar analysis of the PO blowtank showed that the current values of the PI controller is close to the optimum. No changes were thus made for this tank.

Nor were any changes made on the two standpipes investigated. However, the parameters should be changed to at least match the optimal strict settings especially in the first standpipe. Also since all variables effecting them and the standpipes themselves are identical, should the parameters be equal. The difference in models is likely due to disturbances during the tests. Since the tests were old it is possible that they might be inaccurate or faulty, but it is believed they are accurate. No changes have been made on the standpipes since the tests were performed.

6 Conclusion

As a first important step to improve the MPC control of a bleaching plant several tests has been performed to generate models for the delignification stage as well as for several intermediate tanks. An evaluation of sub controllers for MPC relevant valves were also conducted. The results of these investigations are

- The evaluation of sub controllers showed that the valve regulating one of the oxygen flows performed poorly and had to be changed.
- Only one new model could be suggested for the MPC regulating the delignification stage. This model describes the relationship between added $NaOH$ and the pH out of the reactors. It is however unclear if the model is accurate since there was not enough time to evaluate it in further trials.
- Modeling of the reactors was harder than anticipated because of the complex systems and dependence between many factors.
- New values for the PI controllers regulating the level in the intermediate tanks were presented.
- If more accurate models are to be generated in the future, the underlying problems have to be corrected first.

To conclude, there are several aspects to be considered when estimating models for a bleaching process. This thesis has only focused on the most relevant parts of the system, but in order to get the full picture, in depth analyses have to be performed on all levels. This is both time consuming and expensive, and it should thus be ensured that there are no underlying problems in the process that will affect the results before such tests are performed.

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A Additional results for pH and conductivity

The result of monitoring the pH after the O2 reactor as well as the conductivity in the recirculated filtrate are presented in Figure A.1. The values presented are a moving average of the actual values. A comparison of the plots show that the peaks occur in both systems.

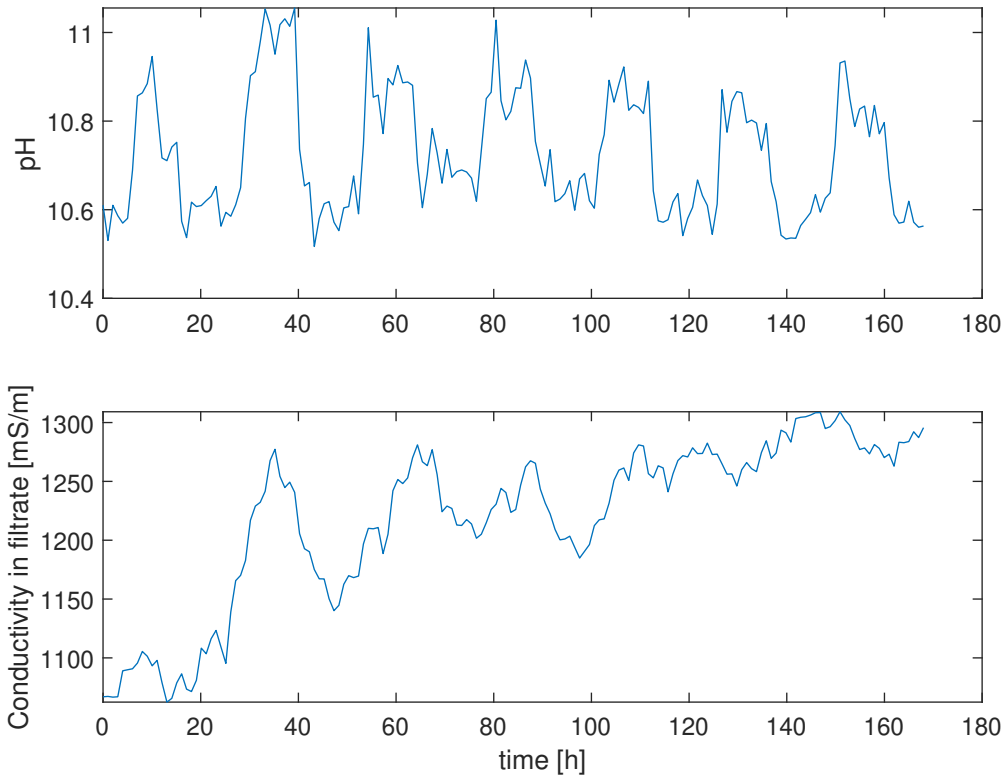

Figure A.1: *Plots pH after the O2 reactor (top) and conductivity of recirculated filtrate (bottom)*