Indirect Adaptive Model Predictive Control of a Mechanical Pulp Bleaching Process using a Smart Delay Time Predictor

by

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B.Sc. in Electrical Engineering, Ain Shams University, 2001

A Thesis Submitted in Partial Fulfilment
of the Requirements for the degree of

Master of Science in Engineering

In the Department of Electrical and Computer Engineering

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This thesis is accepted by the Dean of Graduate Studies

THE UNIVERSITY OF NEW BRUNSWICK

May 25^{th}, 2005

Abstract

The classic way to control a process, in a model based framework, is to obtain a model of the system and then to use it for the design of a controller. A nonlinear time-varying process can be operated in real-time by an indirect adaptive controller. Part of this thesis is devoted to describing the particular structure of such a controller and applying it to a pulp bleaching process. We present and discuss all aspects of controlling a real-world delay time system application, the pulp bleaching process at *Irving Paper Ltd.* The bleaching process was thoroughly studied, and models identified offline as a single-input single-output process then extended to a multivariable process. Then online identification methods were used, and the process was accurately modeled as a first order system plus a variable delay time. This is a difficult process to control, since the delay time varies with pulp flow into and out of the bleaching vessel.

Another major part of the thesis focuses on improving the controller performance by solving the variable delay time problem using a novel a Smart Delay Time Predictor approach and a recursive least squares (RLS) model identifier. This new approach is an extension of the variable delay time estimator technique based on time-variable flow processes. The present work has improved the approach proposed by *Sayda* and *Taylor* [6] in one important respect: the time delay prediction method presented here eliminates the adverse transients occurring in case of the uncertainty in the variable time delay, i.e., it removes transient spikes due to miscalculation of the forced response inside the controller.

The efficacy and robustness of this technique is demonstrated by controlling the pulp bleaching process using an indirect adaptive model predictive control (MPC) algorithm with an RLS identifier and a variable delay time predictor embedded in that controller. This algorithm produces control moves that account for good reference tracking in the presence of disturbances and actuators constraint. Further, a filter is added to the RLS parameter estimator to tackle the problem of small spikes occurring in the input and the output of that controller.

We extended the online identification methods to identify the pulp bleaching process when dealing with it as a multivariate system. Such a model would be used as the basis for multivariable control. However, the poor quality of the resulting model precluded that work.

Acknowledgments

Many people supported me during the completion of this thesis with criticism, helpful assistance and references. This thesis would have never been possible without them. First of all, I would like to particularly acknowledge with thanks the help, patience, friendship, guidance and encouragement of Dr. *James Taylor*, my research supervisor. I think his presence, his introduction to the topic, and the long discussion concerning difficult points in the theory was the best thing that could happen to me in my thesis.

Many thanks to *Atalla Sayda*, PhD candidate, who explained a lot of details to me in this work and helped me whenever I was in need. A special thanks to *John Creighton* who inspired me in MATLAB programming through his suggestions. I would like also to thank all my colleagues at the department for the great atmosphere they all provided, especially Dr. *Idris Gadoura*, *Khaled Ibrahim*, *Mohamed Shawky*, *Mazyar Laylabadi*, *Maira Omana*, *Jing He*, *Xin Ding*, *Salil Joshi* and *Etienne Dupuis*.

Grateful acknowledgment made to *Irving Paper Ltd.* for the financial support provided by them during the whole thesis time.

Last but certainly not least, I owe a special gratitude to my parents Dr. *Mohamed Akida* and Dr. *Laïla Sedky* who have been generous with their encouragement throughout and provided unwavering support for my studies. This thesis is dedicated to them.

Khaled

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Chapter 1

The Mechanical Pulp Bleaching Process

1.1 Introduction

Pulp is the principle raw material for making paper. Paper is made from fibers, and approximately 93% of this fiber coming from wood. Wood comes from two major groups of trees: (i) conifers, more commonly called softwood, make up to 35% of the trees worldwide, (ii) hardwood, which are trees with broad leaves, make up the remaining 65%.

Pulp mills convert the wood chips to pulp. Pulp is the fibrous material produced chemically, mechanically or through a combination of chemical and mechanical means from wood or other cellulose raw material. Pulp mixtures or "furnish" comes from four sources: (i) hardwood pulp (ii) softwood pulp (iii) market pulp, which is the pulp purchased from other mills, and (iv) brook, which is the waste from paper machines that is re-pulped for re-use.

Pulping is a process by which a wood or non wood material is reduced to a fibrous mass. The task can be accomplished by a mechanical means, chemical means or a combination of the two treatments. Currently in North America, 70% of all pulping is chemical. In mechanical pulping, wood fibers are separated by mechanical abrasion and water. The wood is forced against a rotating disc or stone which literally shreds the wood into fibers. The fibers are then washed from the stone or passed out of the refiner. The resulting slurry is screened, cleaned and thickened [1]. Generally, chemical pulp can be bleached whiter than other pulp and will form a stronger paper, but it has a lower yield, requiring more wood. Mechanical pulp is usually not bleached because of the high residual lignin, which

forms the bond that holds fibers together, but it may be brightened. Mechanical pulp is generally weaker, but it requires less wood due to the high yield. Mechanical pulp is still used for paper that require high level of yield, bulk, stiffness and low cost such as newsprint and catalog papers.

1.2 Principles and practices of pulp bleaching

Bleaching is a chemical process applied to cellulosic materials to increase their brightness. Brightness is the reflectance of visible light from cellulose cloth or pulp fibers formed into sheets. Absorbance of visible light by wood pulp fibers is caused mainly by the presence of lignin, one of the principal constituents of wood. Lignin in live wood is colored slightly, while residual lignin remaining after an alkaline pulping process, discussed later, is highly colored. In addition, lignin darkens with age. Bleaching processes increase brightness by lignin removal or lignin decolorization. In the manufacture of mechanical pulp and chemi-mechanical pulp, wood is broken down into fibers with little or no lignin removal and the bleaching of pulp takes place by decolorization. Lignin removal bleaching not only increases the brightness but the brightness stability of the product as well. The pulp is first cooked in a digester. Then the brown stock is washed to remove the black liquor. This stock is screened to remove unwanted particles, including bark and shive, which are fragments of fibrous materials present in pulp or paper, resulting from incomplete resolution during pulping. Finally the stock is cleaned to remove additional unwanted material.

Chemicals commonly used for pulp bleaching include oxidants (chlorine, chlorine dioxide, oxygen, ozone and hydrogen peroxide) and alkali ($NaOH$), and, for mechanical pulp only, a reducing agent, sodium hydrosulfite. Hydrogen peroxide is commonly used as a bleaching agent, and is simply called "peroxide". These chemicals are mixed with pulp suspensions and the mixture is retained at a prescribed pH, temperature and concentration for a specific minimum period of time.

Progress of bleaching is monitored by measuring pulp brightness and residual chemicals. Several methods for measuring the brightness have been developed and used as standards. ISO brightness can be defined as the brightness of paper measured at a wavelength of 457 nanometres under standard conditions. The standard ISO scale can be expressed as "% ISO", for example a sodium hydrosulfite agent (HYDRO) is added if the objective is to produce newsprint in the paper machines. This bleaching agent increases the brightness by 4 to 5%, to accommodate the brightness requirements of the newsprint (55 to 60%

ISO), whereas hydrogen peroxide bleaching yields better pulp from magazine grade paper (brightness 65 to 70% ISO). A4 papers can go up to a brightness of 98% ISO. Reaction times for bleaching chemicals are generally in the range of few minutes to several hours, requiring construction of large towers (reactors) to provide an adequate retention time.

1.3 Flow sheets for peroxide bleaching processes

The industry standard when the brightness target does not exceeds 75% ISO is the medium consistency single-stage peroxide bleach plant. Mechanical pulp is treated with hydrogen peroxide as follows: First, the pulp is treated using pentasodium diethylenetriaminepentaacetic (DTPA), which is added to remove transitional metal ions in the pulp, and it is washed. Conditions include agitation and at least 15 minutes retention time at temperature, ranging from at least $105 - 130\ ^oF$ $(40 - 54\ ^oC)$. Bleach liquor is generally made up in a cascade mixing system and applied to the pulp. Bleach liquor is a mixture of water, sodium hydroxide, hydrogen peroxide, and sodium silicate. The objective of caustic extraction ($NaOH$) is to remove the alkali-soluble portion of the lignin from the woodpulp. Finally, a small amount of lignin binds to cellulose.

Pulp is held in a tower for at least two hours, though retention in excess of this time is also common. In general, a peroxide residual of $5 - 10\%$ of the amount applied is desired. Most systems add sulfur dioxide (SO_2) at the end of the bleaching process, to prevent reversion and for pH adjustment. In summary, three steps are generally required in preparing the bleached pulp: (a) washing the pulp, (b) heating to the desired temperature, and (c) retention to complete the reaction. The bleach plant flowsheet is shown in figure 1.1.

1.4 Factors affecting brightness in peroxide bleaching

Raw material in mechanical pulp is almost without exception wood. Mechanical pulp is made from both softwoods and hardwoods, all of which have different response to peroxide bleaching. Many factors have a major effect on the bleachability of the pulp, and thus on its desired target brightness. Let us discuss some of them and examine their effects.

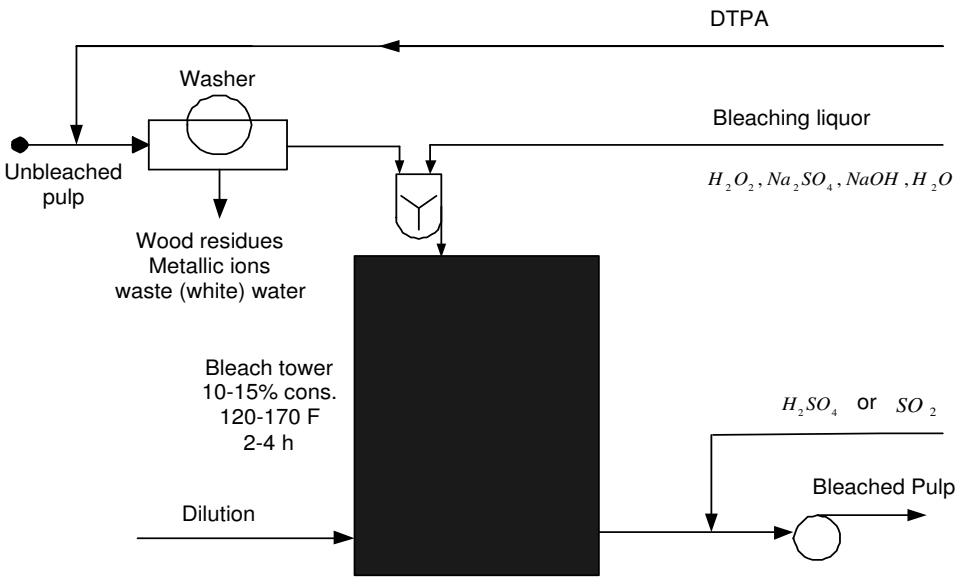

Figure 1.1: Flowsheet for single-stage peroxide bleaching plant [2]

1.4.1 Effect of initial brightness of wood (unbleached pulp)

Initial brightness is highly dependent on the wood species from which the pulp is made. Generally, a higher initial (unbleached) brightness implies a higher bleached brightness where equivalent amounts of bleaching chemicals are applied. Wood used for mechanical pulp should be characterized by good strength, high brightness, absence of color and freedom of other operating problems. The spruces meet these requirements better than other trees in North America and can be used in newsprint without additional brightening. Other favorite softwood trees are hemlock, pine and balsam.

1.4.2 Effect of the pulping process on initial brightness

Mechanical pulping involves a wide diversity of processes. Most mechanical processes use grinders and refiners to separate the wood fiber. Grinding is the oldest method, in which wood logs are forced against a rapidly revolving roughened grindstone and converted into individual fibres. In refining, wood chips are fed between two metal discs (at least one of which rotates) of a refiner and converted to individual fibres. These two processes result in significantly different pulp characteristics. Groundwood pulp has a higher content of fine material due to the abrasive action, whereas refiner pulp has a smaller content of fine material but a higher content of long fibers. As a result, refiner pulping produces much

stronger fibres than stone groundwood. Various types of refined mechanical pulp can be obtained by modifying the refiner pulping process. Thermo-mechanical pulping (TMP) is a modification of a refiner mechanical pulping (RMP) process. If chips are heated to $110 - 130^{o}C$ before refining, they become malleable and do not fracture readily under the impact of the refiner bars. Refining can also be performed under pressure. If the presteaming time and temperature are limited, higher steam pressures can be used in the refiners without reducing pulp quality. At temperatures from $100 - 150\ ^{o}C$ wet lignin softens but does not flow. When hot chips are fiberized in a refiner at high consistency, whole individual fibers are released. A thermo-mechanical pulping process involves three main operation areas [3]:

1. *wood chip pretreatment* consists of chip screening to remove under or oversize material; chip washing to remove rocks, metal and sand; chip steaming to soften lignin binding the fibers so that produced pulps have a greater percentage of long fibres and less shives.

2. *wood chip refining* aims at breaking chips into individual fibres.

3. *pulp processing* aims at enhancing and controlling pulp quality. It consists of: pulp screening and reject refining to remove unrefined fibres bundles; pulp cleaning to remove heavy contaminants; pulp washing to remove wood resins and metallic ions; and pulp bleaching to increase brightness.

Figure 1.2 exhibits the effect of different pulping processes on the final pulp brightness, where the higher the temperature of the pulping process the lower the relative bleachability of the mechanical pulps produced from the wood species. Production of TMP pulps increased dramatically after the process introduction in the early $70's$ because they could be substituted for ground-wood pulps (GWP) in newsprint blends to give a stronger pulp.

1.4.3 Control of H_2O_2 decomposition due to metal impurities

Transition metals act as catalytic decomposition agents when in contact with H_2O_2. The most commonly occurring metals are manganese, iron, copper, aluminium and nickel. The most active decomposition element is manganese. The first step in successful bleaching is to minimize the occurrence of catalytic decomposition. Two methods are used to achieve this goal.

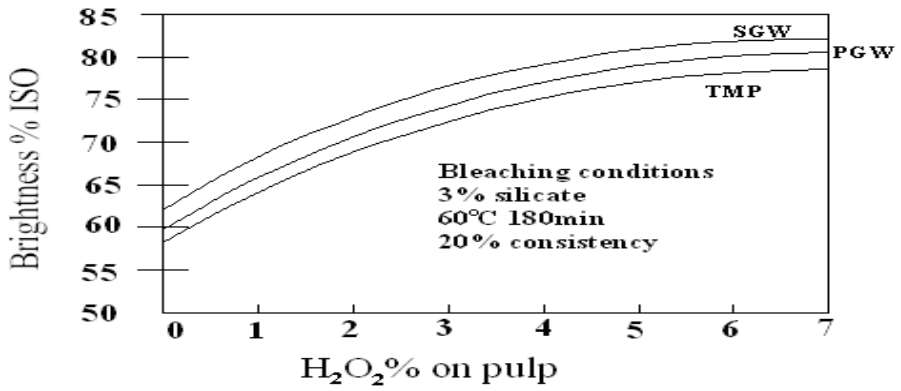

Figure 1.2: Effect of pulping processes on final pulp brightness: Stone Ground Wood (SGW), Pressurized Ground Wood (PGW) and ThermoMechanical Pulping (TMP)[2]

- **Pretreatment of mechanical pulp with organic chelants**
  The purpose of pretreatment of mechanical pulp is to wash off the transition metals present in the pulp before addition of bleach liquor. It is carried out using an organic chelant which forms an organo-metallic complex with the free metal. Typically, DTPA is used in this role. Pretreatment is carried out at low consistency (3-5%) and pH $(4-6)$, after refining or grinding. Two easily measured parameters are used to determine the effect of pretreatment and define the optimal application: brightness and H_2O_2 consumption which is determined by measuring the residual peroxide in the pulp at the discharge point of the bleaching tower. The effect of DTPA is, for example, to increase brightness by up to 3 points and reduce peroxide consumption by 35%. The reduction in peroxide consumption can be important in situations where bleach liquor is reclaimed at the end of the bleaching treatment and recycled to a previous bleaching stage. Figure 1.3 shows the relation between DTPA and the pulp brightness.

- **Stabilization of peroxide bleach liquor using sodium silicate**
  The second approach is to add sodium silicate to the alkaline peroxide liquor. It is a cost effective stabilizer for bleaching and produces two strong effects: it reduces H_2O_2 decomposition occurring during bleaching and also it improves the internal stability of the bleach liquor solution itself. Even with inclusion of a pretreatment to eliminate some of the metals, addition of silicate to bleach liquor leads to a higher brightness for the same peroxide application.

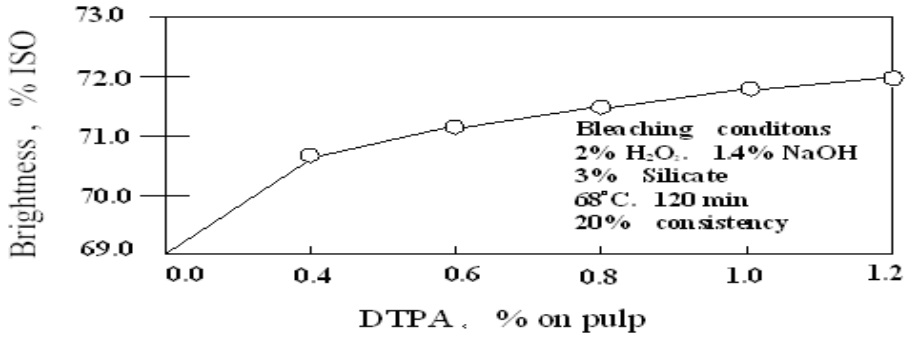

Figure 1.3: Effect of DTPA addition on pulp brightness response [2]

1.5 Primary process variables

1.5.1 Peroxide charge

Brightness response in peroxide bleaching of mechanical pulp is directly related to peroxide application. Increased peroxide dosage leads to increased brightness. For a given set of bleaching conditions, there is a threshold beyond which increased peroxide dosage has a minimal effect on brightness. Figure 1.4 presents the relation between adding peroxide and its impact on the pulp brightness. Clearly dosage levels greater than 5% to 6% lead to little benefit, so any excess H_2O_2 is wasted.

1.5.2 Total alkalinity

The most important interaction for the appropriate control of alkaline peroxide mechanical pulp bleaching is that between peroxide dosage and alkalinity level. Total alkalinity is the pulp bleaching resistance to change in pH. If the alkali charge is too low, inefficient bleaching is likely to result. If it is high, an alkali charge may lead to pulp darkening or yellowing. The pH of pulp slurry immediately after bleach liquor addition in the 10.5 to 12 range. If the initial pH is too high, the rate of peroxide decomposition may exceed the rate of the bleaching reaction, thereby reducing brightness response. If the initial pH is too low, an extended retention time or higher temperature may be required to obtain the same brightness response. Total alkalinity is the sum of all sources of alkali (OH radical)

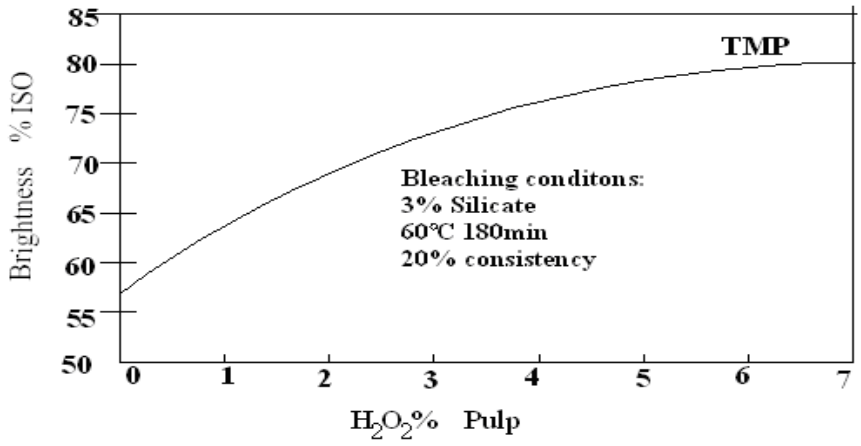

Figure 1.4: Effect of hydrogen peroxide application on pulp brightness [2]

in bleach liquor expressed in terms of sodium hydroxide

$$\%TA = NaOH + 0.115 \times Na_2SO_3$$

A useful way of expressing relationship between H_2O_2 and TA is TA/H_2O_2. The optimum TA/H_2O_2 ratio diminishes as H_2O_2 augments. This influence of the TA/H_2O_2 ratio on pulp brightness is described in figure 1.5, which can be interpreted by the alkali demand from the wood acids present in the pulp. Because this value is constant, it's more significant at low peroxide application than at high peroxide application.

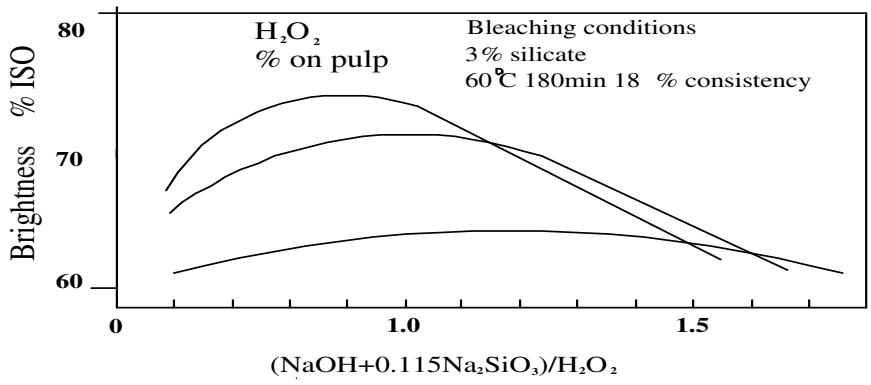

Figure 1.5: Influence of $\frac{TA}{H_2O_2}$ on pulp brightness [2]

1.5.3 Consistency

Consistency can be defined as the percentage of bone-dry fibrous material in any combination of pulp and paper *or* stock (pulp and additives) and water.

$$C = \frac{F}{W} \times 100$$

where C is the consistency of the pulp or stock slurry in percentage, F is the total weight of fibrous material on that amount of pulp and stock slurry, and W is the total weight of a particular amount of pulp or stock slurry.

H_2O_2 bleaching can be carried out over a wide range of consistency, from 4 to 35%. Limitations on bleaching at high consistency have been equipment related: no efficient, commercially available dewatering systems or high consistency mixers existed before the last 10 to 15 years. Two stage peroxide bleaching often incorporates both a medium consistency (15%) stage and a high consistency ($25 - 35\%$) stage to allow maximum liquor recycle. From figure 1.6, at low consistency, not only does GWP require more peroxide to achieve the same brightness, but there is a definite *ceiling* for the brightness response which cannot be exceeded by further peroxide addition. However, from the shape of curves, it is probable that an upper brightness limit will also eventually be reached under higher consistency conditions. A continuous increase in the bleaching response occurs as consistency is increased up to the 40% level. Above this level pulp handling and homogeneous chemical mixing exceed the capabilities of available commercial equipment.

1.5.4 Time and Temperature

Of the variables affecting the brightness response of mechanical pulp, time and temperature are the most closely related. An increase in bleach temperature can compensate for a decrease in retention time, to a point. Conversely, if the bleach temperature is held below $140^o F$ ($60^o C$) extending the retention time produces same brightness response. When TMP is bleached at different temperatures under optimized TA conditions, two limitations are immediately apparent as shown in figure 1.7: (i) At higher temperature, brightness develops rapidly reaching a maximum in 30 minutes or less. (ii) Although brightness development is more rapid at higher temperatures, final brightness is less than that achieved with the same chemical charge at a lower temperature. The rapid decrease in brightness observed for high temperatures (85^o C) bleach is a result of peroxide being consumed totally [2]. This occurs because, at higher temperature, the reaction rates for both bleaching and

decomposition are increased. The effectiveness of transition metals control is imperative to minimize peroxide decomposition.

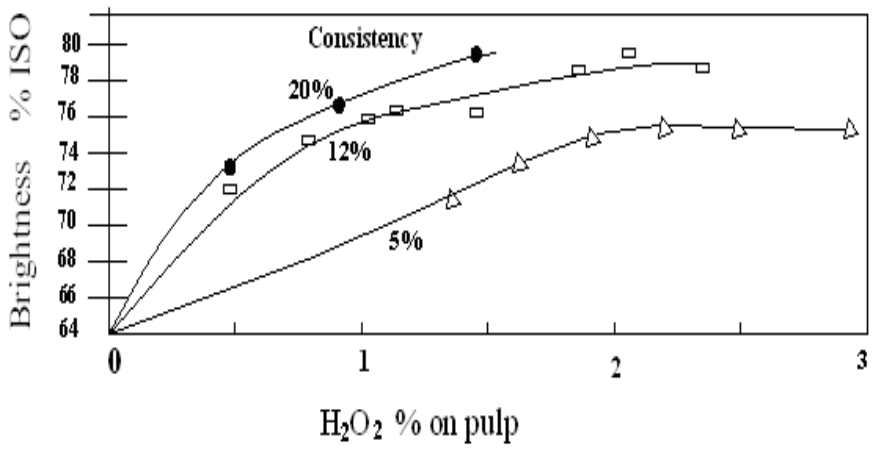

Figure 1.6: Effect of consistency on pulp brightness for *GWP* [2]

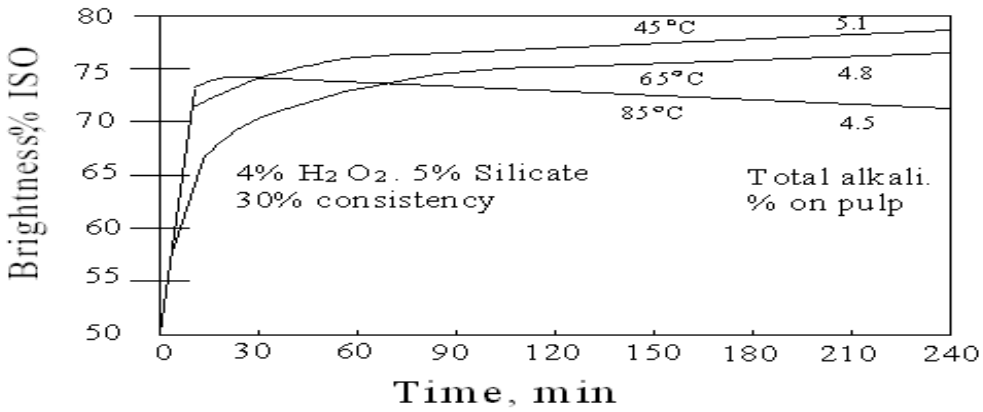

Figure 1.7: The effect of temperature on the rate of brightness development [2]

1.6 Thesis Outline

After a review of the fundamental related to pulp and paper production and the refiner mechanical pulp bleaching process, Chapter 2 describes methods employed to model the process using three different offline system identification algorithms. A discussion about how to model the bleaching tower is presented. An extensive explanation of the idea of the

variable delay time and its calculation inside such a process is presented and illustrated. Chapter 3 presents the idea of indirect adaptive predictive control, its advantages compared to the classic PID controller, the application of the online identification method to model a single-input single-output (SISO) bleaching process, its results and benefits compared to the offline identification techniques. Chapter 4 is devoted to the description of the model predictive controller (MPC) and its extension to be applied as an indirect adaptive controller. Also, we explain the problem of having uncertainty of the calculation of the variable delay time in the bleaching process, with illustrations. A novel Smart Delay Time Predictor used to tackle the problems of adverse transients occurring in case of the uncertainty of the variable time delay, is described and embedded in the adaptive MPC controller. A filter is added to the online recursive least squares algorithm (RLS) parameter estimator to eliminates small spikes appearing in the control output. A robustness study on the controller is taken into consideration. The thesis conclusion is given in Chapter 5.

1.7 Contributions

This thesis describes the development of a useful control strategy for the control of a TMP plant. The manipulated variables are hydrogen peroxide and sulfur dioxide. An indirect adaptive controller is developed based on model predictive control (MPC) because of its simplicity, flexibility and capability of handling problems in one algorithm. Problems due to the uncertainty of the variable delay time in the bleach tower are explained and solved. The main contributions of the thesis are as follows:

- A thorough study of the modeling of the pulp bleaching process using three offline and online identification algorithms, with full descriptions and simulations, was conducted yielding impressive results for modeling the pulp bleaching process. This work was a comparison and an extension of single-input single-output and multiple-input single-output system identification simulations employed in [6].
- A time-varying indirect adaptive predictive controller was designed, that can be executed online (using online identification algorithms, and model predictive control as a controller) and applied for a single-input single-output process where hydrogen peroxide and final pulp brightness are the process input and output respectively.
- A novel time delay prediction method is created to tackle the problem of adverse transients occurring in case of uncertainty of the variable time delay, i.e., it elimi-

nates spikes due to miscalculation of the time delay inside the controller; and (2) a thorough study compared to *Zenger et al* [16] and illustrations of the variable time delay calculation were exhibited. The efficacy and robustness of this technique is demonstrated by controlling the pulp bleaching process using a model predictive control (MPC) algorithm with a variable delay time embedded in that controller. The contributions of this method presented here include the delay time predictor that: (1) is straightforward to implement and to use (2) corrects the uncertainty of the delay time estimator, and (3) is reliable for a broad class of chemical processes.

- A discrete filter was embedded in the RLS parameter estimator was added to suppress the spikes occurring in the controller input and output whenever the setpoint changes. That yields to smooth the peroxide input dosage and the pulp brightness output responses.

Chapter 2

Industrial TMP Bleaching System Identification

2.1 Introduction

Many experimental studies have been carried out on the effect of operating conditions on the final pulp brightness in a peroxide bleaching plant. Residence time, peroxide charge, reaction temperature, inlet pH, stock consistency and SO_2 dosage are generally recognized as the most important operating conditions. To model the peroxide bleaching process, one needs to select a set of variables which is pertinent to the physical and chemical phenomena taking place in the process [4].

There are two main ways to build a mathematical model of the process we are interested in. One way is to build a model that describes relations between input, output and states based on the physical and chemical principles describing the process. That approach could produce a number of differential equations describing the process, called a *non parametric model*. That can be very difficult due to lack of knowledge about what really is happening inside the system, e.g., complicated flow patterns, boundary conditions near the walls of the vessel, etc. [5]. Thus we will consider some aspects of this approach but not attempt to complete such a model. The other way is to try to describe the connection between input and output signals without using detailed knowledge about the system, at least not directly, but instead building a linear "*black box model*" and estimate the unknown parameters. Knowledge about the system in not disregarded, it is used in the process of choosing the right model structure.

2.2 TMP bleaching process mathematical model

Pulp brightness is, of course, the most important variable when discussing the bleaching process. Changes in production rate resulting from variations in the stock flow rate and/or stock consistency affect the residence time in the bleaching tower as well as the chemical demand to achieve the desired brightness gain. Brightness variation of the pulp entering the bleaching plant is a major disturbance to the operation of the plant. Pulp consistency, temperature, chemical charge and inlet pH values determine the bleaching reaction rate. Two categories can describe the bleaching process based on their chemical and physical laws. The first category concerns the chemical kinetics of the bleaching reaction, the second one deals with the dynamics of the pulp transport and mixing in the unsteady flow system, which is composed of the bleaching tower, pipes and storage tanks [6].

2.2.1 Kinetic model

The most important aspect in modeling a bleaching tower is the knowledge of bleaching reaction kinetics. *Moldenius* empirical kinetic model [7] is still a widespread one used to depict the hydrogen peroxide bleaching of mechanical pulps and is given by the following expression:

$$\frac{dK}{dt} = -k \left[\ H_2O_2 \ \right]^{0.67} \left[\ OH^- \ \right]^{-0.23} K^{2.2} \tag{2.1}$$

where K is the chromophores concentration that should be eliminated to increase the pulp brightness, k is the reaction constant, H_2O_2 is the peroxide concentration, and OH^- is the alkaline ion concentration. This equation clearly shows the importance of peroxide concentration and the relationship between peroxide and total alkalinity (OH^-). To predict the brightness of the pulp, a relationship between the light absorption coefficient and brightness is needed. The $Kubelka - Munk$ equation [8] provides a relationship between the absorption coefficient K, the scattering coefficient S, and the brightness R.

$$R = 1 + \frac{K}{S} - \left[\ \frac{2K}{S} + \left(\ \frac{R}{S} \ \right)^2 \ \right]^{\frac{1}{2}} \tag{2.2}$$

The brightness is calculated from the light absorption and light scattering coefficients using the above equation.

2.2.2 Bleach tower model

In order to model the dynamics of a bleaching tower, it is necessary to know the flow pattern of the pulp stock inside the tower. The flow pattern not only determines the residence time distribution of the reacting materials but also controls the effectiveness of the bleaching reaction. Most of mechanical pulp bleaching plants using hydrogen peroxide operate at 20% consistency or higher, as was previously described in section 1.5.3, since higher consistency increases brightening capability. Aside from a little mixing at the inlet and outlet of the retention tower, the pulp stock is nearly in a state of plug flow inside the tower. The retention tower can be represented by a Continuous Stirred Tank Reactor ($CSTR$) followed by a Plug Flow Reactor (PFR) and, then, by a second $CSTR$. The first $CSTR$ can be used to depict the chemical bleaching reaction that takes place in the mixer. In general, we neglect this mixing part of the tower, because the brightness sensor cannot capture its fast time constant response when measuring the output pulp brightness. The plug flow is due to the assumption that the the bleached pulp is assumed to flow inside the tower with no mixing. The second $CSTR$ is due to the mixing the pulp with sulfur dioxide (SO_2) at the bottom of the tower. *Qian* and *Tessier* proved from their simulation results in [4] that the dynamics of the bleached pulp inside the tower can be represented as a delay time dynamics (plug flow) followed by a first order lag dynamics (mixing part). Their simulations also confirm that the sensitivity of the final pulp brightness to the chemical charges is the dominant control variable, and to the initial pulp brightness is the most important disturbance.

2.3 TMP bleaching process system identification

System identification is the field of modeling dynamic systems from experimental data; a model is fitted to the collected data from the real process by assigning suitable numerical values to its parameters [10]. Once the parameters are estimated, the model is validated to recognize if it is an appropriate representation of the process. If not, then another approach or a more complex model structure must be pondered. The system is driven by input variables $u(t)$ and disturbances $v(t)$. The user can control $u(t)$ but not $v(t)$. The output signals are variables which provide useful information about the system. There are many different ways to identify systems. One broad distinction is between *online* and *offline* methods. The online methods give estimates recursively as the measurements are obtained and are the only alternative if the identification is going to be used in an adaptive controller

or if the process is time varying. In many cases the offline methods for simple processes as identifying DC motors give estimates with higher precision and are more reliable, for instance in terms of convergence.

One of the advantages in using system identification is that only basic quantitative knowledge of the process mechanism is required to find a suitable structure for modeling the process input-output relationships. Also, using system identification, dynamic modeling can be realized more easily and in less time than using the mathematical analysis where the development of complex differential equation may be required. Furthermore, some methods do not require special input signals, whereas many "classic methods", discussed in section 2.3.1 to section 2.3.3, depend strongly on having the input of a precise form, e.g., steps, sinusoids or impulses. Other techniques can handle any type of input signal. One requirement of the input signal is that it should excite all modes of the process sufficiently; aside from that, a good identification method should be insensitive to the characteristics of the input signal [12]. The objective of the industrial pulp bleaching system identification is to find some form of mathematical model suitable for the control of a plant, which describes how the input, the output and the disturbances are related. We consider in our plant study the hydrogen peroxide (H_2O_2) and sulfur dioxide (SO_2) dosages as the inputs to the system. The final pulp brightness and the pulp pH are taken as the outputs of the system. We start our approach adopted in this study by using simple offline identification methods as follows:

2.3.1 Least-Squares Method

A popular identification method used is the well known *least-squares method* which can be traced back to Gauss (1809), who used such a technique for calculating orbits of the planets [10, 11]. The basic idea is to minimize the sum of the squares of the error between the observation and its estimate computed as a function of the past observations. The linear regression is the simplest type of parametric model. In the general least-squares problem, it is assumed that "the computed variables", $\hat{y}$, in Gauss terminology is given by the model:

$$\hat{y} = \theta_1\varphi_1(x) + \theta_2\varphi_2(x) + \ldots + \theta_n\varphi_n(x) \tag{2.3}$$

where $\varphi_1, \varphi_2, \ldots, \varphi_n$ are elements of an n-vector of known quantities defining the model structure, and $\theta_1, \theta_2, \ldots, \theta_n$ comprise an n-vector of unknown parameters. Pairs of observations $\{(x_i, y_i), i = 1, 2, \ldots, N\}$ are obtained from an experiment. The elements of the vector $\varphi(x)$ are often called regression variables or regressors while $\hat{y}$ is called the regressed

variable. We will call θ the parameter vector. The problem is to determine the parameters in such a way that the variables $\hat{y}_i$ computed from the model (2.3) and the experimental values x_i agree as closely as possible with the measured variables (experimental data) y_i. The principle of least-squares says that the parameters should be selected in such a way that the loss function

$$J(\theta) = \frac{1}{2}\sum_{i=1}^{N} e_i^2$$

is minimal where

$$e_i = y_i - \hat{y}_i = y_i - \theta_1\varphi_1(x_i) - \ldots - \theta_n\varphi_n(x_i) \qquad i = 1, 2, \ldots, N$$

To simplify the calculations, the following vector notations are introduced:

$$\begin{aligned}
\varphi &= [\varphi_1 \quad \varphi_2 \quad \ldots \quad \varphi_n] \\
\theta &= [\theta_1 \quad \theta_2 \quad \ldots \quad \theta_n]^T \\
y &= [y_1 \quad y_2 \quad \ldots \quad y_N]^T \\
e &= [e_1 \quad e_2 \quad \ldots \quad e_N]^T \\
\Phi &= \begin{bmatrix} \varphi(x_1) \\ . \\ . \\ . \\ \varphi(x_N) \end{bmatrix}
\end{aligned}$$

In the statistical literature the equation errors are often called *residuals*. The least-squares estimates of θ is defined as the vector that minimizes the loss function J which can be written as

$$J(\theta) = \frac{1}{2}e^T e = \frac{1}{2}\|e\|^2 \tag{2.4}$$

where

$$e = y - \hat{y} \tag{2.5}$$

and

$$\hat{y} = \Phi\theta \tag{2.6}$$

According to equation (2.5) the equation error $e(t)$ is a linear function of the parameter vector θ. The parameter θ in such a way that $\|e\|^2$ is minimal can be determined as follows [12]:

$$\theta = \hat{\theta} = (\Phi^T\Phi)^{-1}\Phi^T y \tag{2.7}$$

if $\Phi^T\Phi$ is nonsingular.

Figure 2.1 exhibits data of incremental variables recorded during 2176 minutes from *Irving Paper* mill, where the pulp brightness *(right trace)* increased sharply after a delay time of about 425 minutes, which is the time the pulp took to be bleached inside the bleaching tower, after increasing the peroxide dosage at about 550 minutes *(top left trace)*, and sulfur dioxide SO_2 after 960 minutes *(bottom left trace)*, to destroy the peroxide residual and to reduce the pH of the pulp to between 4 and 5. From these recorded data, the

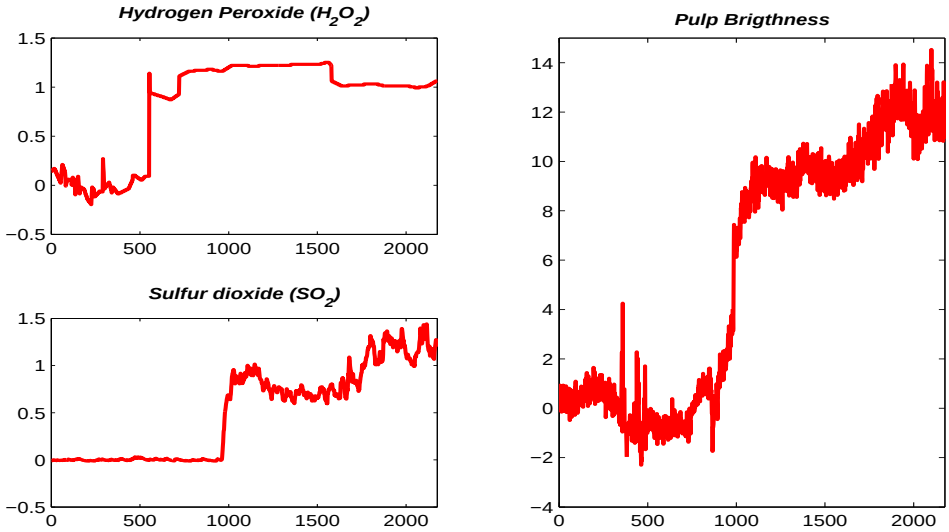

Figure 2.1: Input data (H_2O_2 and SO_2) and output data (pulp brightness)

bleaching process model can be represented as a three stage dynamic process [4, 5]:

- A pure gain K represents the linearized bleaching reaction kinetics, since the reaction is complete when the pulp exits the bleaching tower.
- A long variable delay time T_d results from the plug flow pattern of the bleaching tower.
- A first order dynamics with a time constant τ due to the SO_2 mixing process at the bottom of the tower.

Based on these assumptions, the model structure is defined by $\varphi = [-y(k) \quad u(k)]$. We start by removing the trends in the data (if needed), eliminating the delay time difference between the hydrogen peroxide input and the pulp brightness output, then estimating the

process parameters (i.e. gain and time constant) using system identification methods. Simulation results in figure 2.2 show the model identification using the least-squares method. Let us denote the inputs as U_1 and U_2, whereas the pulp brightness output is called as Y_1.

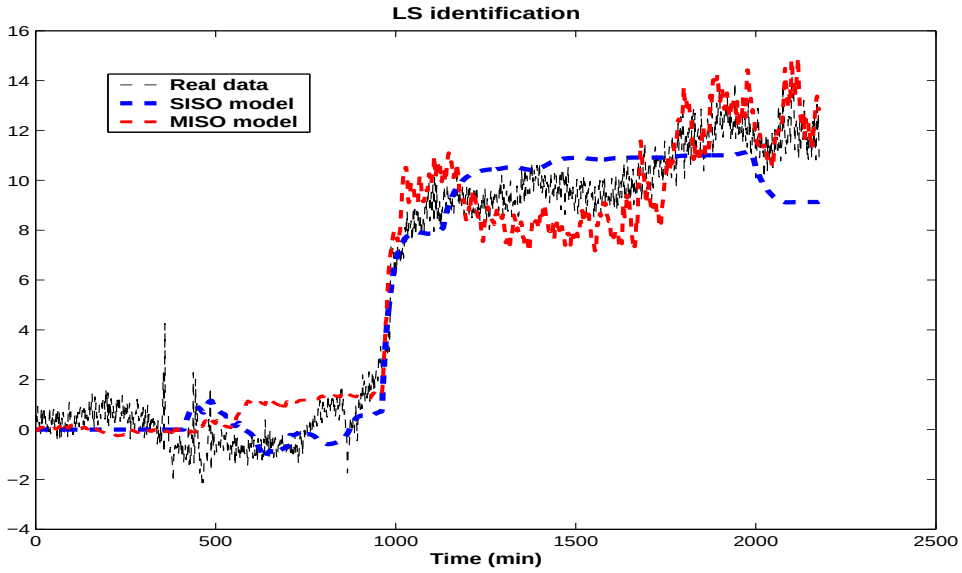

Figure 2.2: Least Squares algorithm for $SISO$ and $MISO$ system models

Two cases are considered: the first case (*dashed line*) deals with the process as a single-input single output (SISO) model, where the peroxide dosage is the input and the final pulp brightness is the output. The result is not entirely accurate due to the noisy data, existence of disturbances and not taking SO_2 effect into account. The gain K equals 8.936 and the time constant is 25 minutes, whereas the delay time is 425 minutes. The transfer function is formed as:

$$Y_1 = \frac{8.936e^{-425s}}{25s+1} U_1$$

The second case (*dotted line*) deals with the process as a multiple-input single output (MISO) model, where SO_2 is the second input variable affecting the identification model. The time constant of the simulated brightness matches closely the actual one of the process, which is in the vicinity of 18 minutes. The H_2O_2 gain equals 1.175 whereas SO_2 gain is

9.53, yielding to the following MISO transfer function

$$Y_1 = \begin{bmatrix} \frac{1.175}{18s+1} & 9.53 \end{bmatrix} \begin{bmatrix} e^{-425s}U_1 \\ U_2 \end{bmatrix}$$

The simulation result is much better compared to the first case, as it captures the effect of the secondary dynamics due to the adding of the SO_2 dosage to the pulp brightness. Let us use another type of data as in figure 2.3 which shows the multiple-inputs multiple-outputs (MIMO) of the pulp bleaching process. we consider the manipulated variables as the *hydrogen peroxide* H_2O_2 and the *sulfur dioxide* SO_2. The controlled variables are scrutinized as the *pulp brightness output* and the pH. We consider the following transfer

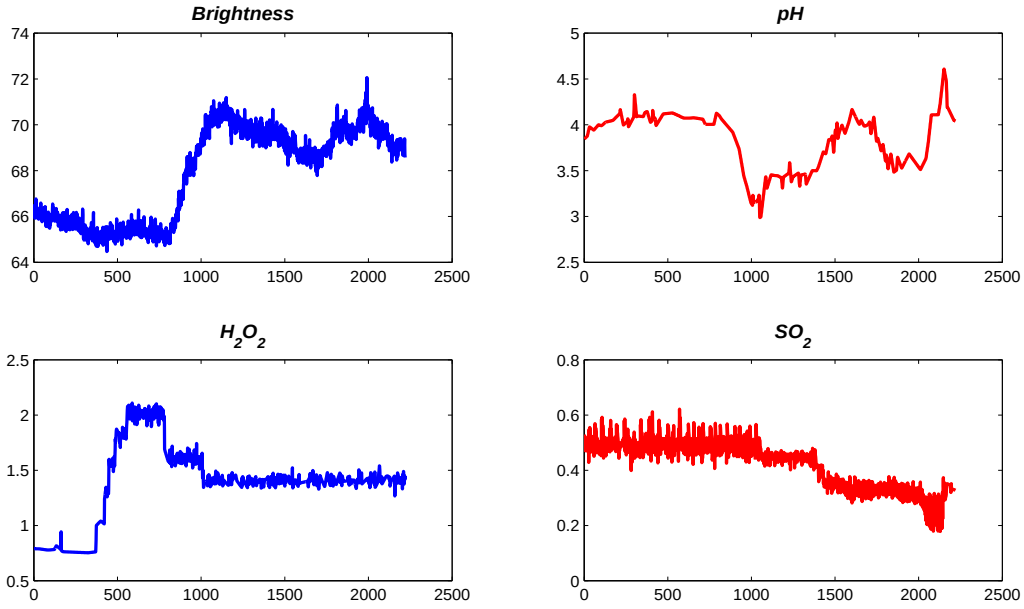

Figure 2.3: Data for a MIMO process

function model, which will be suitable to identify those data, where U_1 and U_2 are H_2O_2 and SO_2 respectively, whereas Y_1 and Y_2 are the pulp brightness and pH respectively:

$$\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} = \begin{bmatrix} \frac{K_1}{\tau s+1} & -K_2 \\ K_3 & K_4 \end{bmatrix} \begin{bmatrix} e^{-sT_dt}U_1 \\ U_2 \end{bmatrix}$$

The model identification results are shown in figures 2.4 and 2.5 This analysis produced the following MIMO transfer function:

$$\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} = \begin{bmatrix} \frac{4.0272}{12.797s+1} & -8.848 \\ -0.873 & -3.9875 \end{bmatrix} \begin{bmatrix} e^{-440s}U_1 \\ U_2 \end{bmatrix}$$

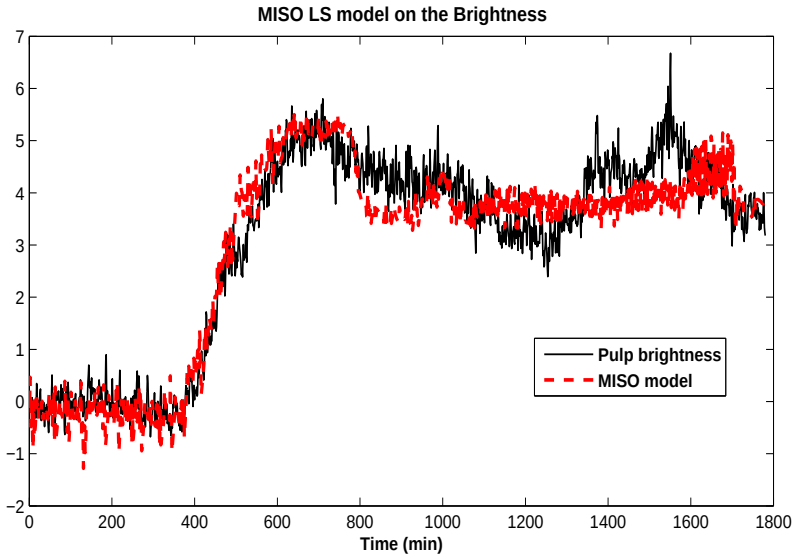

Figure 2.4: Least Squares identification for $MISO$ model on the pulp brightness

Figure 2.4 depicts good results for the identification of the pulp brightness, whereas we can observe from the figure 2.5 that the pH identification is not as accurate. That is due to not taking the effect of $NaOH$ into account while identifying the process. Thus, using the multivariable model to control the process may yield to inaccurate results. So, in chapter 4, we will focus more on controlling a single-input single-output process rather than a multivariable one.

2.3.2 Equation Error Model Structure

The next simplest input-output relationship is obtained by describing the process model as a linear difference equation in both the inputs and outputs:

$$y(t)+a_1y(t-T)+\ldots+a_{na}y(t-naT) = b_1u(t-nkT)+\ldots+b_{nb}u(t-(nb+nk)T)+e(t) \quad (2.8)$$

where k is the number of delay time samples. Since the white noise $e(t)$ here enters as a direct error in the difference equation, the model (2.8) is often called an *equation error model* (structure). We can introduce:

$$A(q) = 1 + a_1q^{-1} + \ldots + a_{na}q^{-na}$$

and

$$B(q) = b_1q^{-1} + \ldots + b_{nb}q^{-nb}$$

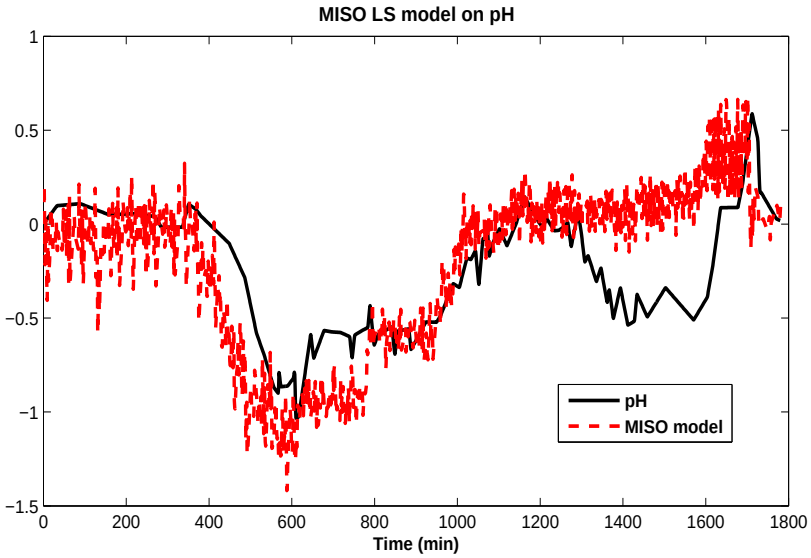

Figure 2.5: Least Squares identification for $MISO$ model on pH

where q is the delay operator in the z-transform notation. Equation (2.8) can be written as follows:

$$A(q)y(t) = B(q)u(t - nk) + e(t) \tag{2.9}$$

The parameters of the ARX model structure are estimated using the least-squares method. We shall also call the model (2.9) an ARX model, where AR refers to the autoregressive part $A(q)y(t)$ and X to the extra input $B(q)u(t - nk)$ (called the exogenous variable in econometrics). When the true noise term $e(t)$ in the ARX model structure is not white noise and na is nonzero, the estimate does not give a correct model. That suggests the use of a more complex model: ARMAX model.

2.3.3 ARMAX Model Structure

The basic disadvantage of equation (2.9) is that lack of adequate freedom in describing the properties of the disturbance term. We could add flexibility to that by describing the equation error as a moving average of white noise. This gives the model:

$$A(q)y(t) = B(q)u(t - nk) + C(q)e(t) \tag{2.10}$$

with

$$C(q) = 1 + c_1 q^{-1} + \ldots + c_{n_c} q^{-n_c}$$

The parameters of the ARMAX model structure are estimated using a prediction error method. In view of the moving average (MA) part $C(q)e(t)$, this model will be called ARMAX.

Results and comments

Figure 2.6 illustrates the ARX and ARMAX identification methods for a SISO model. We computed the output y_{model} that results when the model is simulated with the input u. The result is plotted together with the corresponding measured pulp brightness output data (y_{data}). The percentage of the output variation that is explained by the model

$$fit = 100 \times (1 - \frac{1 - \|y_{model} - y_{data}\|}{\|y_{data} - mean(y_{data})\|}) \tag{2.11}$$

is also computed and displayed. The fit for the ARX model (model m_1) using a first order dynamic model equals 73.24, whereas the fit for the ARMAX model (m_2) is 71.68. The fit in both models are almost similar but are still not high and accurate because of not taking the effect of the second input of the process (SO_2) into consideration.

Figure 2.7 illustrates the ARX and ARMAX identification methods for a MISO model,

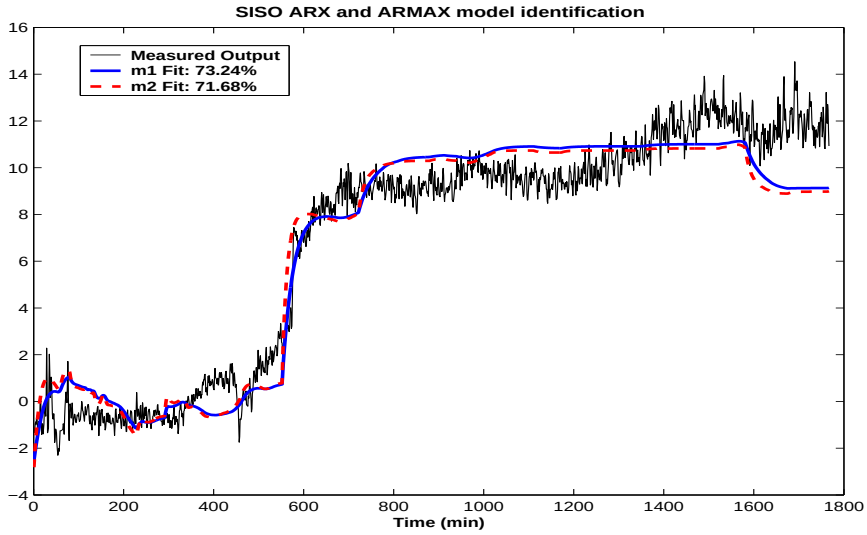

Figure 2.6: ARX and ARMAX models for a SISO system model

where the fit for a first order dynamic ARX model (model $m1$) equals to 83.05, whereas the fit for the ARMAX model (model $m2$) is 82.13. The model in this case fit better than the previous one in figure 2.6 which shows the importance of adding the SO_2 as a second input to the bleaching process.

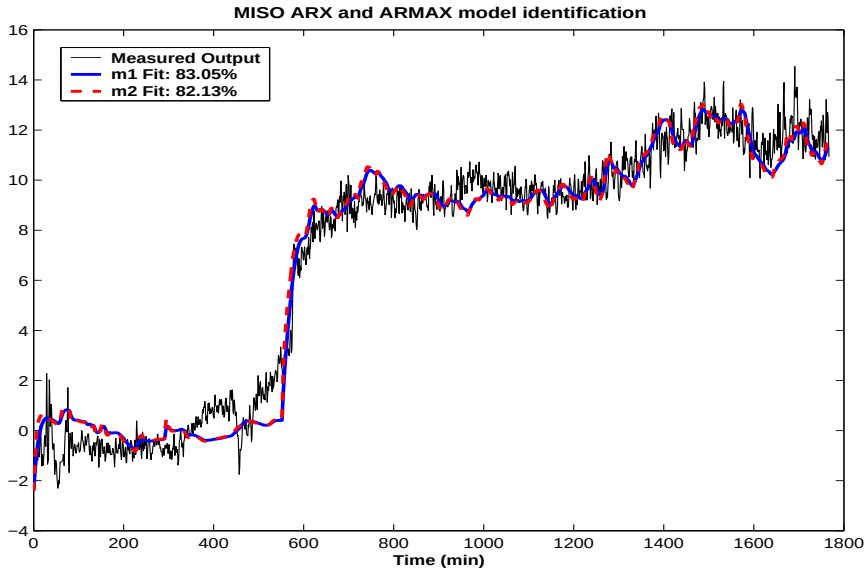

Figure 2.7: ARX and ARMAX models for a SISO system model

2.3.4 Offline system identification Conclusion

Simulation results in the previous three offline identification methods show the effectiveness of using such methods to identify a complex process such as the pulp bleaching process where using the system identification toolbox to identify the process as ARX and ARMAX models have proven to be successful for time-varying long delay time processes as long as we eliminate the delay time samples from the identified data. MIMO least-squares algorithm yields to significant results. As a conclusion, offline identification should be compared to other online identification methods while dealing with adaptive control systems which needs online identification algorithms to deal with online time-varying processes. Those methods will be discussed in chapter 3.

2.4 Delay time estimation

2.4.1 Introduction

A traditional modeling technique for a unit operation is to describe the process as a combination of basic idealized models such as perfect mixers and plug flow vessels. The dynamics of a continuous flow process is dependent on the mass flow rate. The time constant of the process is determined by the flow rate through the vessel, the liquid volume

in it and the degree of mixing. In traditional design, the process is usually assumed to be in a nominal operation point so that the flow rates and volumes are constant, but this assumption is generally not valid. Because of disturbances and intentional changes in the pulp production and utilization rates, the flow rate through the process is not always constant.

One may model a *plug flow vessel*, through which the process material is assumed to flow without any mixing occurring, as a pure time delay. The concentration of the solute at the outlet of the vessel is the same as at the inlet a certain time ago [13]. Under steady flow conditions, the delay time can be calculated by dividing the volume in the vessel by the flow rate. We define the residence time of the feed material as the time between entering at the input of the flow system to exiting at the output. The bleaching tower, which is the main contributing element in the continuous flow system of the bleaching process, can be represented by a by a plug flow reactor followed by a continuous stirred tank reactor. The division of the residence time into two parts is motivated by a simple model of a flow system. The plug flow of a system is modeled as a transportation part e^{-sT_d}, and the part where the material is mixed is modeled as a first-order lag $\frac{1}{1+s\tau}$.

2.4.2 Delay time estimation literature

In chemical reaction engineering, the concept of residence time distribution (RTD) is fundamental to reactor design. RTD is the exit age distribution of fluid molecules leaving a reactor. The classical residence time distribution covers only the case of stationary operating conditions, i.e., the flow rate through the system and the liquid volume in the system are constant. However, there is a strong practical need to consider processes under unsteady operating conditions also, because of disturbances and intentional changes in the process operation. To consider such systems with time-varying behavior brings the classical RTD theory beyond its scope, and extensions to the theory are needed [14].

The volume and flow through vessels and tanks, or more generally the quantities influencing the dynamics of the continuous flow system, are time varying and this in fact is an additional difficulty in the identification procedure. For example, the flow in an industrial process is subjected to changes both for random reasons, such as disturbances of various kinds, and intentionally, when the production and/or utilization is increased or decreased. Similarly, the volume changes in a buffer vessel, and the purpose is to control the flow variations.

2.5 Estimation of the delay time based on inflow

Zenger [15, 16] introduced the concept of a variable delay function, which can be used to estimate the delay time even though the flows and volume are varying. Models with varying liquid volumes are more complex than those with varying flow rates only, and it is often impossible to find a transformation that would change the representation into one with constant coefficients. Consider the case of a plug flow vessel, in which both the input and output flow rates and the liquid volume change. The model equations are:

$$\dot{V}(t) = Q_i(t) - Q_o(t) \tag{2.12}$$

$$\int_{t-T_d(t)}^{t} Q_i(\tau)d\tau = V(t) \tag{2.13}$$

where $Q_i(t)$ and $Q_o(t)$ are the inflow and outflow rates in liters per minute, $V(t)$ is the liquid volume in the plug flow vessel, and $T_d(t)$ in equation (2.13) can be understood as the past time when material exiting the vessel entered, i.e., the present delay time. We can justify equation (2.13) as follows:

1. It is the property of an ideal plug flow vessel that during the time that a particle stays in the vessel, the volume $V(t)$ of new liquid must enter, $V(t)$ being the total liquid volume at the time that the particle leaves the vessel.

2. all *old material* must have left the vessel when the observed particle is at the outlet of the vessel.

3. When the original particle is at the bottom of the tank, we want to know t_1 which is $t - T_d(t)$, which is the time at which this particle has entered the vessel; thus we consider $Q_i(t)$ in this case.

An illustration of the previous explanation is shown in figure 2.5, where t_o stands for the initial time the particle entered the vessel, whereas t_f is the time the particle leaves the vessel. By differentiating equation (2.13) it is easy to derive:

$$\frac{d}{dt}\left[\ \int_{t-T_d(t)}^{t} Q_i(\tau)d\tau\ \right] = \frac{d}{dt}V(t)$$

Then

$$Q_i(t) - Q_i(t - T_d(t)) * (1 - \dot{T}_d(t)) = \dot{V}(t)$$

From equation (2.12): $$Q_i(t) = Q_o(t) + \dot{V}(t)$$

$$Q_o(t) + \dot{V}(t) - Q_i(t - T_d(t)) * (1 - \dot{T}_d(t)) = \dot{V}(t)$$

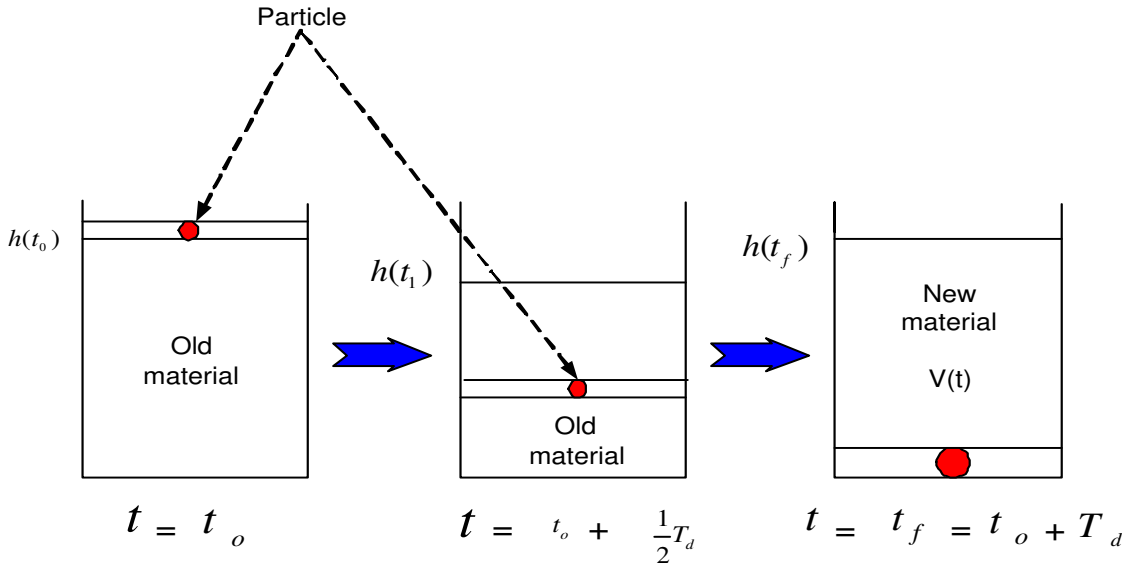

Figure 2.8: Estimation of the delay time based on the inflow

So

$$1 - \dot{T}_d(t) = \frac{Q_o(t)}{Q_i(t - T_d(t))}$$
$$\dot{T}_d(t) = 1 - \frac{Q_o(t)}{Q_i(t - T_d(t))} \tag{2.14}$$

Zenger proposed [16] solving equation (2.14) to determine the delay time numerically. This problem has one deficiency, namely, we cannot predict exactly the delay time initial condition to solve this differential equation. That yields to inaccurate results in the calculation of the delay time.

2.6 Prediction of the delay time based on the outflow

As shown in equation (2.13), we can *estimate* $T_d(t)$ by integrating the pulp inflow backward in time until that integral equals the present volume. Alternatively, we can also *predict* the variable delay time $T_{dp}(t)$ by integrating the pulp outflow forward in time until the integral equals the present volume. This is expressed as follows:

$$\int_t^{t+T_{dp}(t)} Q_o(\tau)d\tau = V(t) \tag{2.15}$$

where $V(t)$ and $t + T_{dp}(t)$ are respectively the present volume and the predicted time at the instant t. Equation (2.15) can be understood as the definition of the "predicted delay

time" as follows: If a *new particle* enters at time t and $V(t)$ is the corresponding volume in the vessel, then $T_{dp}(t)$ corresponds to that future time when a volume of liquid $V(t)$ has exited the vessel. However, predicting the pulp outflow $Q_o(t)$ is difficult for the following reason: the paper-making operators would have to specify their future need for pulp, which is not practical. An algorithm can be realized to determine the delay time either backward as in equation (2.13) or forward as in equation (2.15) as follows:

1. Store the pulp inflow ($liters/minute$) and bleaching tower level ($meters$) over a time interval equal to the maximum retention time of the tower, with a sampling time h equal to 1 $minute$.
2. Calculate the pulp volume in the tower which equals the level of the pulp times the cross section area of the tower.

Backward delay time estimation (equation (2.13))

3. Measure the volume at time t and set a counter $k = t - h$.
4. Integrate the inflow backward from k to t.
5. If the integration results equal to the volume at time t then stop and $T_d(t) = t - k$, else set $k = k - h$ and goto step 4.

Forward delay time prediction (equation(2.15))

6. Measure the volume at time t and set a counter $k = t + h$.
7. Assume future outflow and integrate it forward from t to k.
8. If the integration result equals to the volume at time t then stop and $T_{dp}(t) = k - t$, else set $k = k + h$ and goto step 8.

Either algorithm can be used for identifying the bleaching process delay time using offline data, but it will cause some problems while using it for the real-time control, since T_{dp} and thus the future outflow is required but difficult to predict. Those problems will be discussed in chapter 4. Figures 2.9 and 2.11 show the volume and the pulp inflow for two data sets obtained from *Irving Paper*. Figures 2.10 and 2.12 exhibit the pulp inflow and both the estimated and the offline predicted delay time for two data sets.

2.7 Conclusion

The purpose of the chapter was to compare the effectiveness of either using bleaching process mathematical model or system identification to model such a process. Due to the complexity of the this process, system identification was proposed and the system was modeled as first order system plus a variable delay time. Three offline identification techniques were described and simulated yielding to moderate results in the SISO model and significant one in case of the MIMO model. The estimated and predicted variable delay time, based on the pulp inflow and outflow respectively, were presented, illustrated and calculated separately out of the identification algorithm.

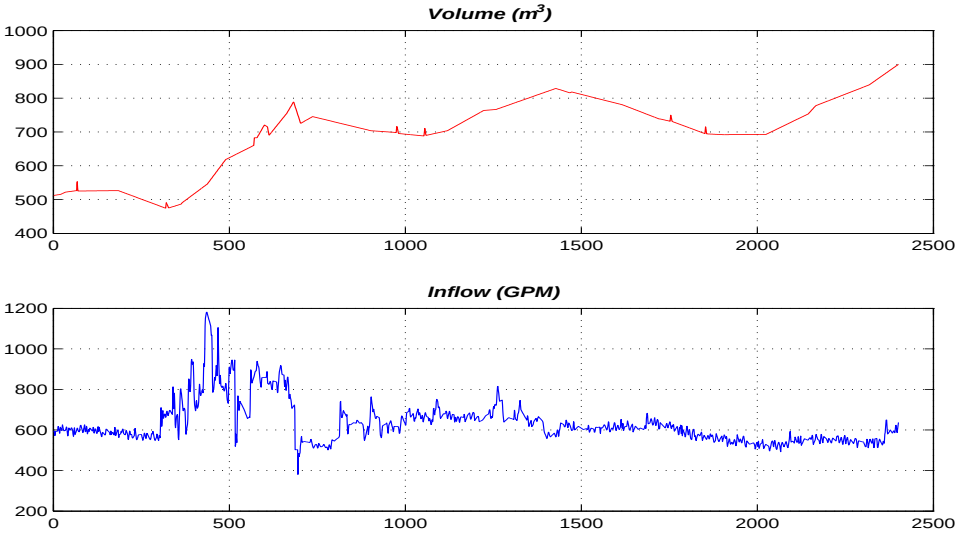

Figure 2.9: Volume and inflow of the first data set

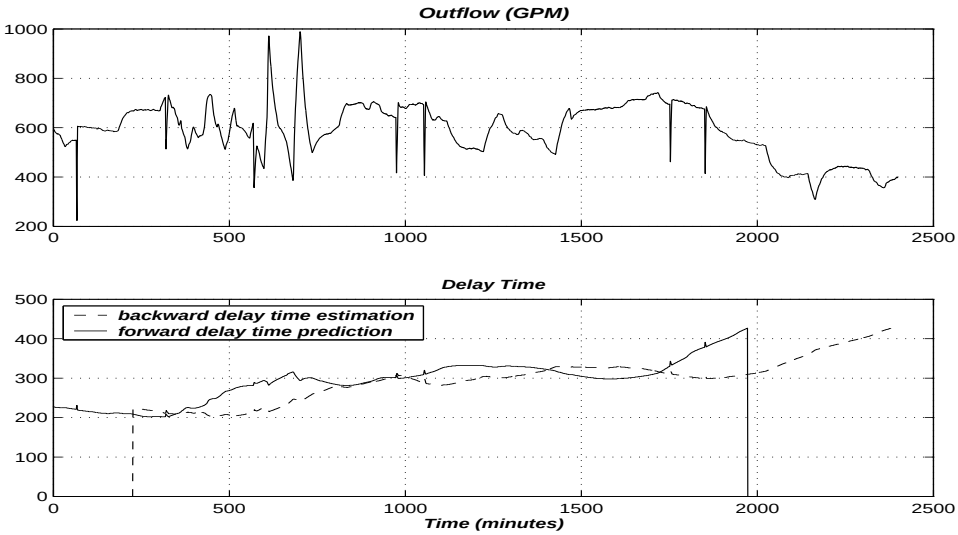

Figure 2.10: Estimated and predicted delay time, first data set

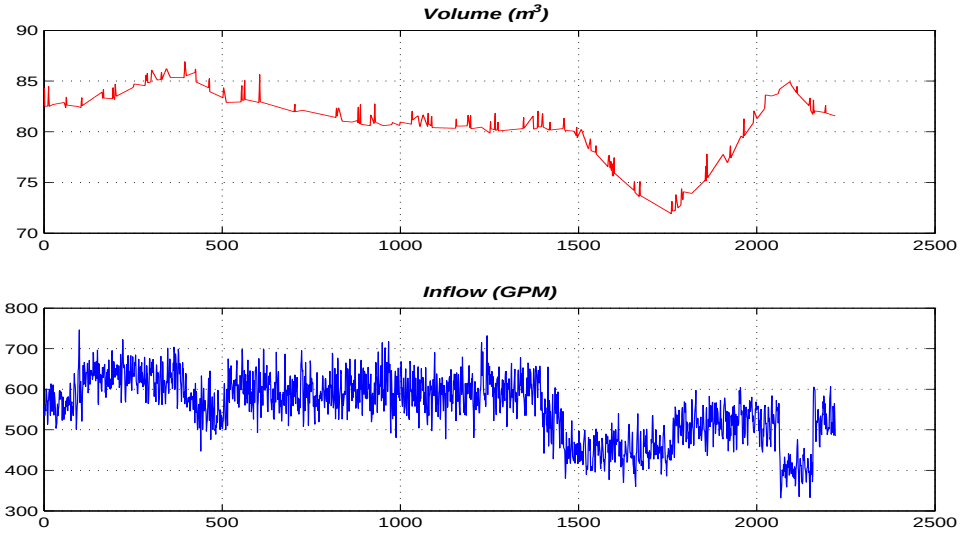

Figure 2.11: Volume and inflow of the second data set

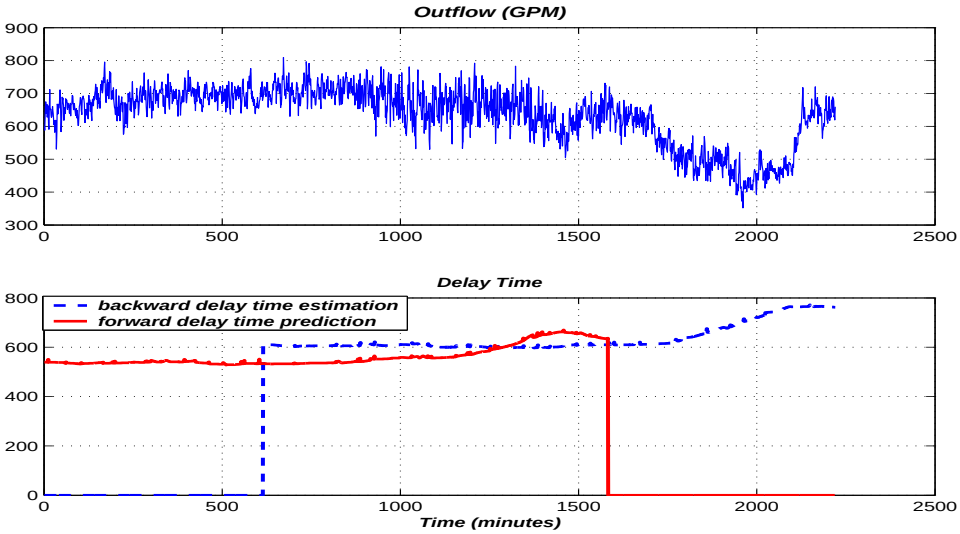

Figure 2.12: Estimated and predicted delay time, second data set

Chapter 3

Indirect Adaptive Predictive Control

3.1 Introduction

Broadly speaking, *process control* refers to mechanisms for automatically maintaining the conditions of a mechanical, chemical, or electrical *process* at specific levels and to neutralize random *disturbances* caused by external forces. A process can be virtually any collection of objects or material with measurable and modifiable characteristics such as, a car traveling at a certain speed, or a power line transmitting electricity at a certain voltage. The conditions or state of a process are generally measured in terms of *continuous process variables*, such as flow rates, temperatures, and pressures that can change at any time. In a basic process control system, a *sensor* measures a process variable, a computer decides how to correct the *error* between the actual and desired values, and an *actuator* such as a valve or a motor carries out the controller's decision to force the process variable to follow the desired trajectory. The resulting change is then remeasured by the sensor and the whole sequence of operations repeats in an ongoing *feedback* or *closed loop*.

3.2 Terminology

Many authors use different terms for the same concepts. For example, the process variable is also known as the *controlled variable* since it is the object of the controller's effort. But since that quantity is resulting from other physical phenomena involved in the process, it is sometimes described as the *process output*. The signal that the controller sends to the actuator is sometimes called the *controller output* or the *process input* the actuators in turn apply it to the process. Other authors refer to it as the *control effort*, the

corrective action, or the *manipulated variable* since it represents the quantity manipulated directly by the controller. The desired value that the controller endeavors to reach for a special process variable is almost universally known as the *setpoint*, while it is occasionally called the *reference value*. The procedure that the controller employs to determine its next control effort is diversely referred to as the *control law*, the *control algorithm*, or the *control equation*. In the same vein, an actuator that implements the controller's decision is sometimes called the *final control element*. If the control law is an algebraic equation, it almost always includes several coefficients that can be set by the designer to prescribe how hard the controller is required to work at eliminating the error between the process variable and the setpoint. These *controller parameters* can be adjusted to match the controller's performance specification (e.g., risetime, percent overshoot). This operation is accordingly known as *tuning*, and the adjustable parameters are frequently called *tuning parameters* or *tuning constants*.

For example, the basic *proportional controller* uses a percentage of the past error as the next control effort, assuming that a larger error needs a larger control effort (and similarly for small errors). Exactly what *gain* the controller should use to multiply with the error to compute the control effort is a matter of tuning. A higher gain would be appropriate for a sluggish process, whereas a lower gain would be necessary to prevent over-correcting a process that is more sensitive to the controller's effort [17].

3.3 Adaptive control

In every language, "to adapt" means to change a behavior to confirm to new circumstances. Intuitively, an adaptive controller is thus a controller that can modify its behavior in response to changes in the dynamics of the process and the character of the disturbances. Since ordinary feedback also attempts to reduce the effects of disturbances and plant uncertainty, the question of the difference between feedback control and adaptive control arises.

In practice there are many different sources of variation, and they are usually due to a mixture of different phenomena. The underlying reasons for the variation are in most cases not fully understood. When the physics of the process is reasonably well known (as for airplanes), it is possible to determine suitable controller parameters for different operating conditions by linearizing the models and using some methods for control design. This is the common way to design autopilots for airplanes, and this approach is usually

not considered to be adaptive control. Most industrial processes are very complex and not well understood; it is neither possible nor economical to make a thorough investigation of the causes of the process variations and account for them as in flight control. Adaptive controllers can be a good alternative in such cases [23].

An adaptive controller is "a controller with adjustable parameters and a mechanism to adjust the parameters" [21, 23]. It can tune its own parameters or otherwise modify its own control laws so as to accommodate fundamental changes in the behavior of the process [17]. The controller is inherently nonlinear because of the parameter adjustment mechanism.

3.3.1 Problems with Traditional PID Control

Non-adaptive controllers are generally "good enough" for most industrial process control applications. The universal proportional-integral-derivative controller or PID loop is especially simple and easy to implement. And though its operations are somewhat simplistic by the standards of modern control theory, a PID loop can be remarkably effective at keeping the process variable close to the setpoint.

The simplicity of the PID controller also makes it fairly easy to understand and easy to diagnose when it fails to perform as desired. Tuning a PID controller is a relatively straightforward operation that can be accomplished with a few empirical tests that have remained essentially unchanged since the $1940s$ (Ziegler and Nichols, 1942 [18]). There is also a variety of well-developed techniques for extending the effectiveness of PID loops in more challenging applications such as gain scheduling for setpoint dependent processes and the Smith Predictor for deadtime-dominant processes [19].

However, even with these enhancements a PID controller leaves considerable room for improvement. Once tuned, it can only control the process if its behavior remains unchanged. If the behavior of the process changes appreciably after start up, the controller may no longer be able to compensate the error when a load disturbs the process variable or a setpoint changes. If the mismatch between the process behavior and the controller's original tuning becomes severe, the closed-loop system may even become unstable as the controller alternately overcorrects, then undercorrects the error until a failure occurs.

The traditional way to cope with time-varying process behavior is to manually retune the loop whenever its performance degrades. That may work if the variation is slow, but

repeatedly tuning and retuning a loop can be tedious and time consuming, especially if the process takes hours to respond to a tuning test, which is the case in a TMP bleaching tower. Tuning rules also require at least some training to apply properly, so many PID controllers end up poorly tuned when implemented by inexperienced operators. In extreme cases, plant operators will deactivate a poorly tuned controller when a disturbance occurs, then reactivate it once they have dealt with the disturbance manually. That strategy defeats the very purpose of feedback control.

3.3.2 Advantage of adaptive control

Convenience is one of the most compelling reasons to replace PID loops with adaptive controllers. A controller that can continuously adapt itself to the current behavior of the process relieves the need for manual tuning both at startup and thereafter. In some cases, manual retuning may not even be possible if the behavior of the process changes too frequently, too rapidly, or too much. A setpoint-dependent or nonlinear process can be particularly difficult to control with a fixed parameter controller since it reacts differently to the controller's efforts depending on the current value of the setpoint. A pH process, for example, becomes more efficient near the required level, yielding to less use of bleaching chemicals to achieve a given change in the pH. It is possible to equip a traditional controller with a different set of tuning parameters for each possible value of the setpoint (a strategy known as gain scheduling), but each parameter set has to be manually adjusted. An adaptive controller can perform that chore automatically.

Self tuning control has been used for many applications since the mid-$1970's$, mainly in the process industry. Applications are found in the areas of pulp and paper, as explained in the thesis, chemical reactors and autopilots. Self-tuning regulators and adaptive controllers in general have found their main uses in three categories of applications: (i) processes with long delay times, (ii) processes where feedforward can be used, and (iii) processes with dynamics and/or disturbances which have time-varying characteristics. The main reason why self-tuning and adaptive control have great superiority in those cases is that in order to achieve good control of those types of processes it is crucial to have models of the process to be controlled and/or the disturbances. The estimator part of the self-tuning controller can produce an estimate of the process and disturbances and use that information in the design.

An adaptive controller, being inherently nonlinear, is more complicated than a fixed-

gain controller in the case of normal feedback control. Before attempting to use adaptive control, it is therefore important to investigate whether the control problem might be solved by constant-gain feedback. In the literature on adaptive control there are many cases in which constant-gain feedback can do as well as an adaptive controller. One way to proceed in deciding whether adaptive control should be used in sketched in figure 3.1. For more details about adaptive controllers, the reader can refer to [20, 21, 22, 23, 24].

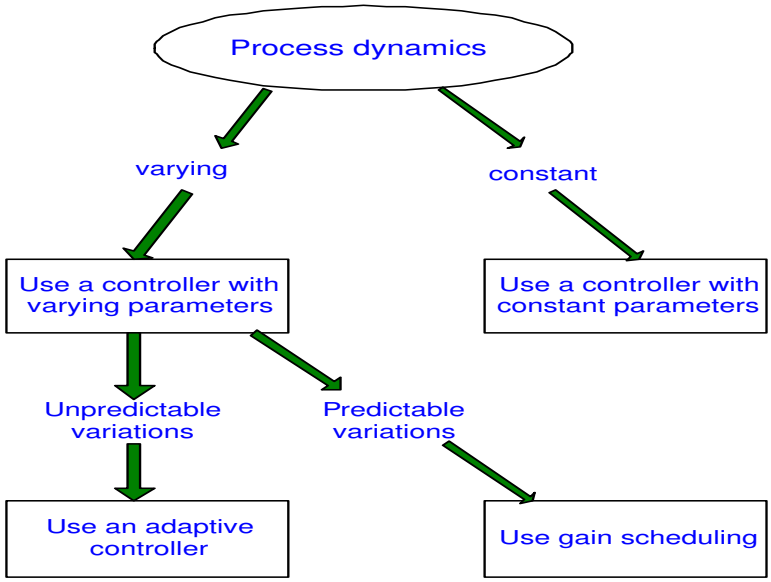

Figure 3.1: Procedure to decide what type of controller to use [23]

The basic ideas and components of self-tuning regulators, or more generally adaptive controllers, are discussed as follows: The design of a controller contains several parallel steps:

1. Generating specifications for the closed-loop system
2. Determining a model for the process to be controlled
3. Deciding on a design method
4. Calculating the parameters of the controller

An adaptive control system can be thought as having two loops. The inner loop consists the process and an ordinary feedback controller. The parameters of the controller are adjusted by the outer loop, which is composed of a recursive parameter estimator and a design evaluator. Notice that the system may be viewed as an automation of process

modeling and design, in which the process model and the control design are updated at each sampling period. The updating loop for the controller parameters can be switched off as soon as the estimated parameters have converged to their final values, i.e., when the controller has tuned or adjusted itself to the specifications of the process. The result is a *self-tuning regulator*. However, if the process is changing over time it is necessary to continuously update the process parameters and the controller parameters. We then have an *adaptive controller*. This implies that a self-tuning regulator is an adaptive controller if the parameter updating is not switched off. Self-tuning regulators are thus a special class of adaptive controllers. Figure 3.2 depicts an indirect self-tuning regulator or an indirect adaptive controller depending on the parameter update strategy. Its structure and blocks are described below.

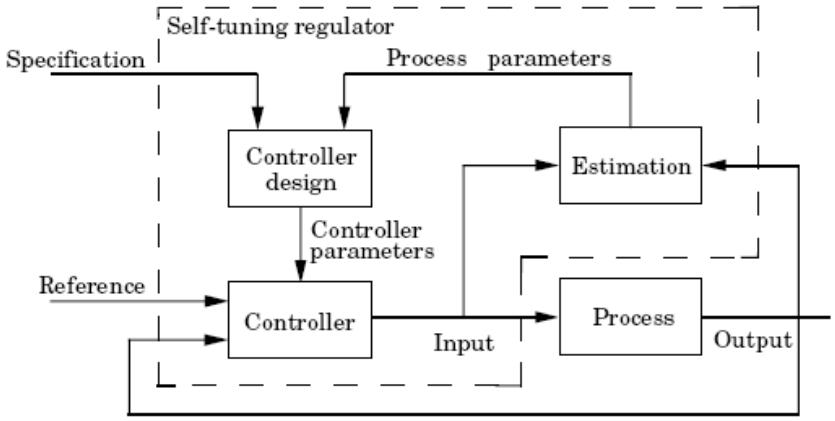

Figure 3.2: Indirect self-tuning regulator [23].

- **Estimation**

  Estimation can be performed continuously or on a regular or irregular basis, depending on the process and requirements. In digital implementations, which are most common, different sampling rates can be used for the controller and the estimator. It is also possible to use hybrid systems in which control is performed continuously and the parameters are updated discretely. Parameter estimation can be done in many ways as will be discussed in the next section and also in the appendix: *Recursive Least Squares* (RLS), *Least Mean Squares* (LMS), and *Normalized Least Mean Squares* (NLMS) algorithms. The system shown in figure 3.2 is thus a very rich structure. A straight forward approach is to estimate the parameters of the transfer function of the process. This gives an *indirect adaptive algorithm*. The controller

parameters are not updated directly, but rather indirectly via the estimation of the model of the process.

- **Controller Design**
  This block represents an online solution to a design problem for a system with known parameters. This is the *underlying design problem*. Such a problem can be associated with most adaptive control schemes, but it is often given indirectly. To evaluate adaptive control schemes, it is often useful to find the underlying design problem, because it will give the characteristics of the system under the ideal conditions when the parameters are known exactly.

- **Controller**
  This block is an implementation of the controller whose parameters are obtained from the control design. The *model predictive control* (MPC) scheme (explained in chapter 4) is very flexible with respect to the choice of the underlying design and estimation methods. Many different combinations have been explored. The controller parameters are updated indirectly via the design calculations in the indirect self-tuning control shown in figure 3.2 [23].

3.4 Online System Identification Algorithms

3.4.1 Introduction

Fluid-dynamic systems are inherently nonlinear and are subject to a combination of coherent and random unsteady disturbances. As a result, accurate low-order dynamic models are difficult to obtain for real-time control of such systems. Also, in many least-squares methods it is assumed that all data samples are already recorded, which is not convenient for online modeling. That was already discussed in chapter 2. Therefore, controllers implementing adaptive online system identification are ideally suited to flow control problems. In online identification the algorithms must run continuously as new measurement data is flowing in. Two points are of interest: the first one is how to develop a recursive form of the least squares estimation algorithm. The second is how to give more weight to the "new" data. Recursive Least Squares (RLS) algorithm will be discussed and applied to identify the time-varying pulp bleaching process where the parameter vector is updated every time a new data sample is measured [25]. Least Mean Squares (LMS) and Normalized Least Mean Squares (NLMS) algorithms will be discussed in the appendix.

3.4.2 Recursive Least Squares algorithm

In least-squares estimation, unknown parameters of a linear model are chosen in such a way that the sum of the squares of the difference between the actually observed and the computed values is a minimum. The form of the model is:

$$y(t) = -a_1 y(t-1) - a_2 y(t-2) - \ldots - a_n y(t-n) + b_0 u(t) + \ldots + b_m u(t-m) \tag{3.1}$$

which can be written in terms of the regression vector

$$\phi^T(t) = \begin{bmatrix} -y(t-1) - y(t-2) \ldots - y(t-n) & u(t) \ldots u(t-m) \end{bmatrix} \tag{3.2}$$

and the parameter vector

$$\theta(t) = \begin{bmatrix} a_1 & a_2 & \ldots & a_n & b_0 & \ldots & b_n \end{bmatrix} \tag{3.3}$$

as

$$y(t) = \phi^T(t)\theta \tag{3.4}$$

This translates into finding the parameters that minimizes the following loss function

$$V(\theta, n) = \frac{1}{2}\sum_{i=1}^{n}(y(i) - \phi^T(i)\theta)^2 \tag{3.5}$$

where $y(i)$ is the instantaneous output signal and $\phi^T(i)$ is the regression variable vector. Solving for the minimizing parameters we get the closed form solution as follows [26]:

$$\hat{\theta} = (\sum_{i=1}^{n}\phi(i)\phi^T(i))^{-1}(\sum_{i=1}^{n}\phi(i)y(i)) \tag{3.6}$$

Most of the time we are interested in real-time parameter estimation, therefore it is computationally more efficient if we update the estimates recursively as new data becomes available online. The recursive form is given by [26]:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + L(k)(y(k) - \phi^T(k)\hat{\theta}(k-1)) \tag{3.7}$$

where

$$L(k) = P(k)\phi(k) = P(k-1)\phi(k)(1 + \phi^T(k)P(k-1)\phi(k))^{-1} \tag{3.8}$$

and

$$P(k) = (1 - L(k)\phi^T(k))P(k-1) \tag{3.9}$$

where $P(k)$ is normally referred to as the covariance matrix.

Equation (3.7) updates the estimates at each step based on the error between the model output and the actual output. The structure is similar to most recursive estimation schemes. In general most have similar parameter update structure and the only difference is the update gain $L(k)$. $L(k)$ defines how to correct the previous estimate based on new measurement data. The scheme can be viewed as a filter that averages the data to come up with optimal estimates. Averaging is a good strategy if parameters of the model are constant in nature. However, many times the parameters that we are estimating are time-varying and we are interested in tracking the variations [26]. In the next section the generalized RLS for time-varying parameters is discussed.

Recursive least square estimation with forgetting

If the values of the parameters of a system change abruptly, periodic resetting of the estimation scheme can potentially capture the new values of the parameters. However, if the parameters vary continuously but slowly a different heuristic but effective approach is popular. That is the concept of "forgetting" in which older data is gradually discarded in favor of more recent information. In least-squares methods, forgetting can be viewed as giving less weight to older data and more weight to recent data. The "loss-function" is then defined as follows:

$$V(\hat{\theta}, n) = \frac{1}{2}\sum_{i=1}^{n} \lambda^{n-i}(y(i) - \phi^T(i)\hat{\theta})^2 \tag{3.10}$$

where λ is called the forgetting factor and $0 < \lambda < 1$. It operates as a weight which diminishes for the more remote data. The scheme is known as least-squares with exponential forgetting and θ can be calculated recursively using the same update equation but with $L(k)$ and $P(k)$ defined as follows:

$$L(k) = P(k-1)\phi(k)(\lambda + \phi^T(k)P(k-1)\phi(k))^{-1} \tag{3.11}$$

and

$$P(k) = (1 - L(k)\phi^T(k))P(k-1)\frac{1}{\lambda} \tag{3.12}$$

The main difference with the classical least-squares method is how the covariance matrix $P(k)$ is updated. In the classical RLS the covariance vanishes to zero with time, losing its capability to keep track of changes in the parameter. In equation (3.12) however, the covariance matrix is divided by $\lambda < 1$ at each update. This slows down fading out of the covariance matrix. In general, exponential convergence in the constant case implies certain

degree of tracking capability in the time varying case. Normally, λ value is usually set between 0.95 and 1.

The RLS with forgetting has been widely used in estimation and tracking of time-varying parameters in various fields of engineering. However, when excitation of the system is poor this scheme can lead to the covariance"wind-up" problem. During poor excitation old information is continuously forgotten while there is very little new dynamic information coming in. This might lead to the exponential growth of the covariance matrix and as a result the estimator becomes extremely sensitive and therefore susceptible to numerical and computational errors. This problem has been investigated by many researchers in the field and several solutions, mostly ad hoc, have been proposed to avoid covariance "wind-up". The idea of most of these schemes is to limit the growth of covariance matrix, for example by introducing an upper bound. A popular scheme uses a time-varying forgetting factor [27]. During low excitations, the forgetting factor is closer to unity to enhance the performance of the estimator. In another approach, an on/off method along with a time-varying forgetting factor for improved performance is used. The concept of resetting the covariance matrix during low excitations is another possible approach.

Summary of the RLS Algorithm

1. Set $k = 1$ and assign a value to λ
2. Compute the filter gain with the forgetting factor λ

$$L(k) = \frac{P(k-1)\phi(k)}{\lambda + \phi^T P(k-1)\phi(t)}$$

3. Compute the true estimation error

$$e(k) = y(k) - \phi^T \hat{\theta}(k-1)$$

4. Update the estimate of the coefficient vector

$$\theta(k) = \theta(k-1) + L(k)e(k)$$

5. Update the covariance matrix with the forgetting factor λ

$$P(k) = \frac{1}{\lambda}(P(k-1) - L(k)\phi^T(k)P(k-1))$$

6. Increment k by 1 and go back to step 2

3.5 Results and implentation comments

3.5.1 RLS estimation

Figure 2.3 in chapter 2 presented data collected for MIMO process of the pulp bleaching process. We assumed in our case that the process is described by the single-input single output (SISO) system where the manipulated variable is $U_1 = hydrogen\ peroxide\ H_2O_2$ and the controlled variable is $Y_1 =$ the *pulp brightness output*. Using the RLS algorithm, figure 3.3 depicts the first order model identification where a time delay of 440 minutes is occurring after adding the peroxide dosage in the top of the bleaching tower, till the pulp brightness increases. This figure shows the time domain performance for system identification using RLS, where the plus + signal represents the actual output and the dashed one represents the estimated output of the model. It is observed that a significant error convergence leads almost overlapping of the two signals, with a gain of 5.1 and a time constant of 32 minutes. The transfer function can be written as follows:

$$Y_1 = \frac{5.1e^{-440s}}{32s+1} U_1$$

To validate our identification, we use the command *lsim* in MATLAB to simulate the time response of the discrete linear bleaching system to the H_2O_2 input, using the transfer function mentioned above. Figure 3.4 shows the validation result, where the model succeeded to track the pulp brightness increase at the right time. The identified model does not track accurately the pulp brightness data after 1200 minutes due to fluctuations in the brightness.

3.5.2 S-function RLS Implementation

We use a specifically structured function (S-function) of MATLAB in our simulation experiments. S-function can simulate the dynamics of a system, but it is relatively difficult to use correctly. In most basic sense, S-functions are simply MATLAB functions using a special calling syntax that enables us to interact with Simulinks equation solvers. This interaction is very similar to the interaction that takes place between the solvers and built-in Simulink blocks. The form of an S-function is very general and can accommodate continu-

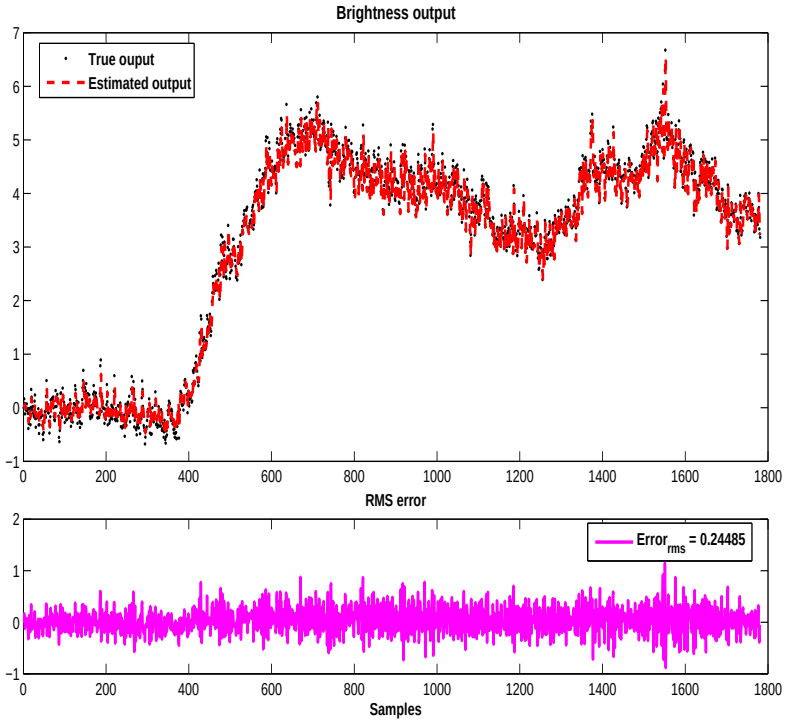

Figure 3.3: Performance of the RLS algorithm

ous, discrete, and hybrid systems. As a result, nearly all Simulink models can be described by S-functions. An advantage of using S-functions is that we can build a general purpose block that we can use many times in a model, varying parameters with each instance of the block and integrating with our own analysis and simulation routines.

The RLS estimator presented in Section 3.4.2 is simulated by using S-function under Simulink where we initialize the covariance matrix and the forgetting factor as $P(0) = 10000I$ (the higher the value of the covariance matrix initial condition, the more the identified model parameters tends to converge to the right values of the process paramaters) and $\lambda = 1$ respectively. We include an S-function block defined by an M-file S-function code into an Simulink model, and excite the plant to be estimated with a 1 Hz square wave. Referring to the first data set in chapter 2 where the first order model has a gain of 8.936 and a time constant of 25 minutes, and converting the parameters to z-transform yields to the transfer function model shown in figure 3.5, where the gain and the time constant equals 0.3266 and -0.9635 respectively. Those values are almost similar to the one of the process (gain = 0.3522 and time constant = -0.9606). We show the Simulink block diagram in figure 3.5 and the experiment results displayed in the scopes of figure 3.6.

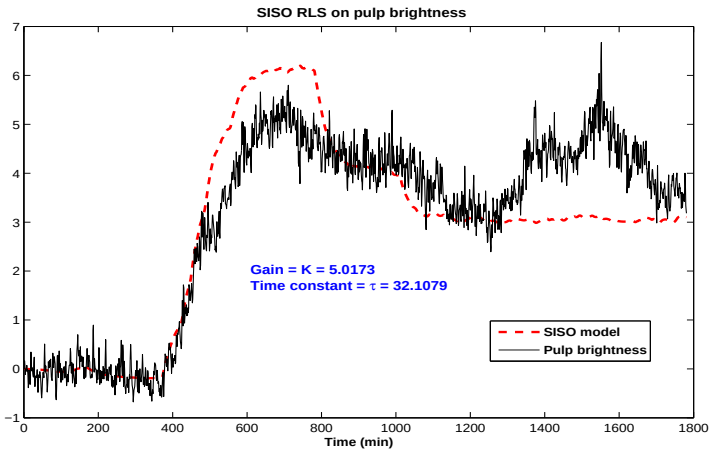

Figure 3.4: RLS algorithm for SISO system model

3.6 Conclusion

The indirect adaptive control design and the Recursive Least squares (RLS) method for plant estimation were discussed. Simulation studies for the estimator algorithm was mainly undertaken after describing how to use MATLAB S-function. From the simulation, it can be concluded that online identification algorithms work well for such a complex process. RLS algorithm shows impressive identification models. To validate this method, the lsim MATLAB command was used to simulate the time response of the discrete linear bleaching system to the H_2O_2 input, using the identified transfer function model.

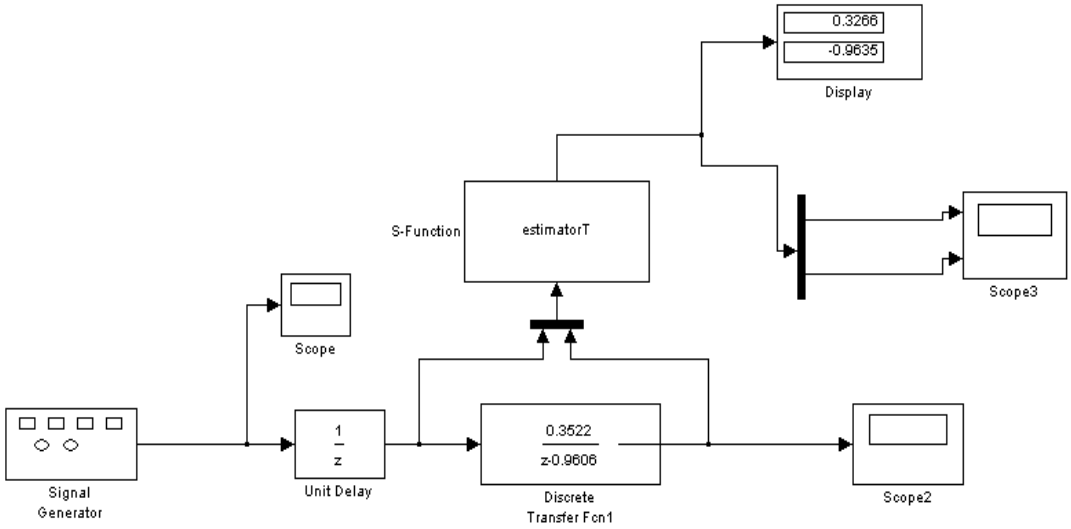

Figure 3.5: Simulink block diagram of RLS parameter estimator

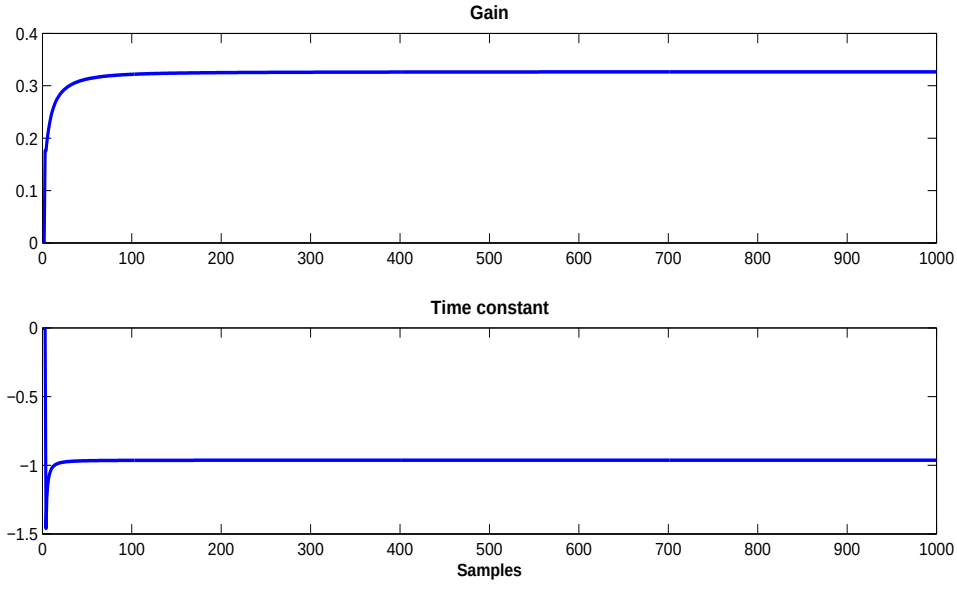

Figure 3.6: Simulation results of the model parameters

Chapter 4

Model Predictive Control

Model Predictive Control (MPC) refers to a class of algorithms that compute a sequence of manipulated variable adjustments in order to optimize the future behavior of a plant. Originally developed to meet the specialized control needs of power plants and petroleum refineries, MPC technology can now be found in a wide variety of application areas including chemicals, food processing, automotive, aerospace, metallurgy and pulp and paper [28]. Although modern optimal control theory provides an elegant and powerful solution to the problem of controlling an unconstrained linear plant, it had little impact on control technology development in the process industries. The most significant of the reasons cited for this failure include: failing to deal with constraints, process nonlinearities, model uncertainty (robustness), unique performance criteria and cultural reasons (people, education, etc.). MPC was developed in the process industries in the 1960's and 70's, based primarily on heuristic ideas and input-output step and impulse response models proposed by *Richalet et al* in 1976 [29] and then summarized in a 1978 *Automatica* paper [30]. The solution software was referred to as IDCOM, an acronym for Identification and Command. The basic principle of MPC is to solve an open-loop optimal control problem at each time step. The decision variables are a set of future manipulated variable moves and the objective is to minimize deviations from a desired trajectory; constraints on manipulated, state and output variables are naturally handled in this formulation. Feedback is handled by providing a model update at each time step, and performing the optimization again. A major reason for the success of MPC is the relative ease with which it may be used to control nonlinear multivariable processes with dead time. The greatest drawback is its need for an appropriate model of the process to be available [32]. We already have dealt with such a problem in chapter 3.

4.1 Dynamic matrix control strategy

The MPC methodology yields satisfactory performance if it is able to satisfy the following requirements: to guarantee stability and particularly to be robust, to be as efficient as possible, to achieve the desired performance criteria, and to be easy to implement and operate in real time through use of digital computers. Dynamic matrix control DMC, a particular MPC method, is used in the pulp bleaching process due to its ease and efficiency. Its basic strategy is as follows [32]:

4.1.1 Prediction

The process model utilized in the DMC formulation is the step response of the plant, while the disturbance is regarded as a constant over a specified horizon N_p (prediction horizon). The discrete-time response of the plant is:

$$y(t) = \sum_{i=1}^{\infty} g_i \Delta u(t-i)$$

where g_i are the sampled output values for the step response and $\Delta u(t) = u(t) - u(t-1)$. The predicted values along the horizon will be:

$$\hat{y}(t+k|t) = \sum_{i=1}^{\infty} g_i \Delta u(t+k-i) + \hat{n}(t+k|t)$$

$$= \sum_{i=1}^{k} g_i \Delta u(t+k-i) + \sum_{i=k+1}^{\infty} g_i \Delta u(t+k-i) + \hat{n}(t+k|t) \tag{4.1}$$

As regards the disturbances, their value are considered to be the same as at instant t along all the horizon, that is, to be equal to the measured value of the output (y_m) minus the the one estimated by the model ($\hat{y}(t|t)$). This is described as follows:

$$\hat{n}(t+k|t) = \hat{n}(t|t) = y_m(t) - \hat{y}(t|t) \tag{4.2}$$

Then equation (4.1) can be written as:

$$\hat{y}(t+k|t) = \sum_{i=1}^{k} g_i \Delta u(t+k-i) + \sum_{i=k+1}^{\infty} g_i \Delta u(t+k-i) + y_m(t) - \hat{y}(t|t)$$

$$= \sum_{i=1}^{k} g_i \Delta u(t+k-i) + f(t+k) \tag{4.3}$$

where $f(t+k)$ is the free response of the system, that is, the part of the response that does not depend on the future control actions and is given by:

$$f(t+k) = y_m(t) + \sum_{i=1}^{\infty} (g_{k+i} - g_i) \Delta u(t-i) \tag{4.4}$$

For a stable process, the coefficients g_i of the step response tend to be constant after N_p sampling periods, which yields to an approximation in equation (4.4) as follows:

$$f(t+k) = y_m(t) + \sum_{i=1}^{N_p} (g_{k+i} - g_i)\Delta u(t-i) \tag{4.5}$$

Computing the prediction along the prediction horizon ($k = 1, \ldots, N_p$), with N_u control actions, yields equation (4.3) to be:

$$\hat{y}(t+N_p|t) = \sum_{i=1}^{N_u} g_i \Delta u(t+N_p-i) + f(t+N_p) \tag{4.6}$$

Defining the system's *dynamic matrix* as:

$$G = \begin{bmatrix} g_1 & 0 & \ldots & 0 \\ g_2 & g_1 & \ldots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ g_{N_u} & g_{N_u-1} & \cdots & g_1 \\ \vdots & \vdots & \cdots & \vdots \\ g_{N_p} & g_{N_p-1} & \cdots & g_{N_p-N_u-1} \end{bmatrix}_{N_p * N_u}$$

it can be written that:

$$\hat{y} = GU + F \tag{4.7}$$

Note that G is made up N_u (the control action) columns of the system's step response compatibly shifted down in order, $\hat{y}$ is a N_p-dimensional vector comprising the system prediction along the horizon, U depicts the N_u-dimensional vector of control increments, and F is the free response vector.

4.1.2 Cost function and reference trajectory

The set of future control values is calculated by optimizing a specific criterion J in order to keep the process as close as possible to the reference trajectory $\omega(t+k)$ which is the desired set point or a close approximation of it. It is normally defined as a smooth transition from the current value of the output $y(t)$ towards the known reference by means of the following first order system:

$$\omega(t+k) = \alpha\, \omega(t+k-1) + (1-\alpha) r(t+k) \qquad k = 1 \ldots N_p \tag{4.8}$$

where α is a parameter between 0 and 1 (the closer to 1 the smoother the transition) that constitutes an adjustable value that will influence the dynamic response of the system, and $r(t+k)$ is the constant future reference.

The specific criterion usually takes the form of a quadratic function (cost function) of errors between the prediction output signal and the prediction reference trajectory plus a weighted quadratic input term as follows:

$$J = \sum_{j=1}^{N_p} [\hat{y}(t+j|t) - \omega(t+j)]^2 + \sum_{j=1}^{N_u} \lambda[\Delta u(t+j-1)]^2 \tag{4.9}$$

where λ is a positive constant that can be used to tune the DMC controller to achieve the required performance. If there are no constraints, the solution to the minimization of the cost function $J = e^T e + \lambda U^T U = (GU + F - \omega)^T (GU + F - \omega) + \lambda U^T U$, where e is the vector of future errors along the prediction horizon, and U is the vector composed of the future control increments $\Delta u, \ldots, \Delta u(t + N_u)$, can be obtained analytically by computing the derivative of J and making it equal to 0, which provides the general result [32]:

$$U = (G^T G + \lambda I)^{-1} G^T (\omega - F) \tag{4.10}$$

An explicit solution can be obtained if the criterion is quadratic, the model is linear and there are no constraints, otherwise an iterative optimization method has to be used. The control signal $u(t|t)$ is sent to the process, while the subsequent control signals calculated are rejected, because at the next sampling instant $y(t+1)$ is already known and the output prediction is repeated with this new value and all sequences are brought up to date. In other words, given the control signal $\Delta u(t) = K(\omega - f)$, where K is the first row of matrix $(G^T G + \lambda I)^{-1} G^T$ (figure 4.1), we observe that if there are no future predicted errors, that is, if $(\omega - f) = 0$, then there is no need for a control move, since the objective will be fulfilled with the evolution of the process; otherwise, there will be an increment in the control action proportional (with a factor of K) to the future error. Notice that the action is taken with respect to *future* errors, not *past* errors, as is the case in conventional feedback controllers.

4.1.3 Constrained DMC

The flexible constraints handling capabilities of MPC are very attractive for practical applications. Due to safety reasons, it is necessary to keep a safe zone around the operating points of a typical process, since the effect of perturbations can make the process violate constraints. As a matter of fact, all actuators saturate. Figure 4.2 shows a typical control loop with actuator saturation. Ignoring the presence of saturation can cause long undesirable transients in the closed loop. Those transients are due to the controller states having "wound up" to large values [33]. The constraints acting on a process originating

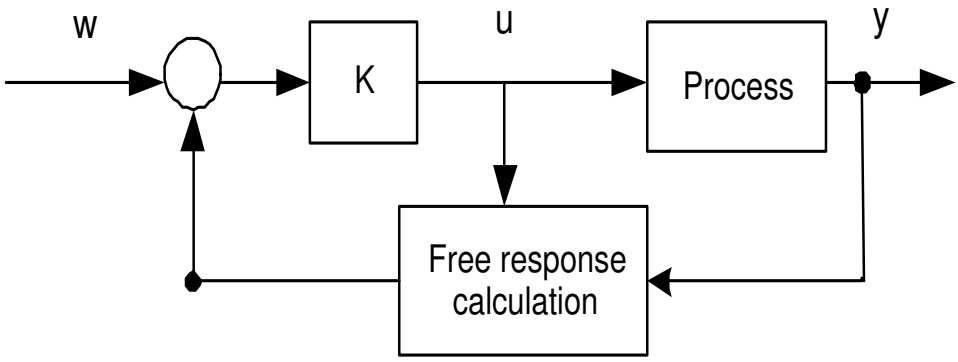

Figure 4.1: DMC control law [32]

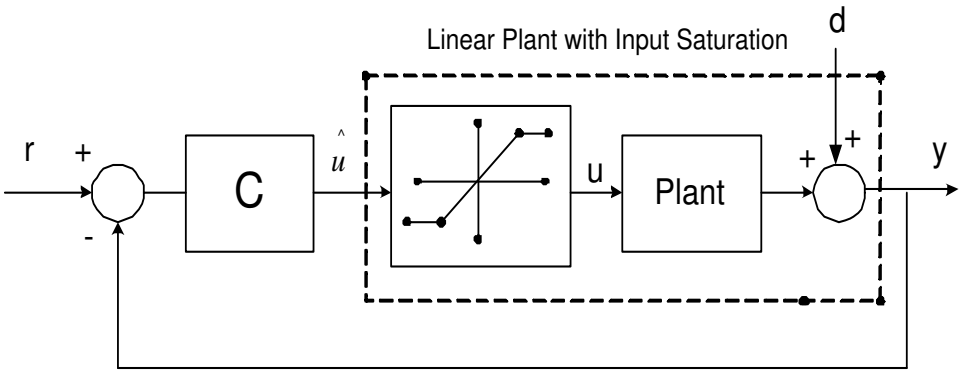

Figure 4.2: Control system with saturation on the plant input

from amplitude limits in the control signal, where Δu is the manipulated variable before saturation, and u_{min} and u_{max} are the minimum and maximum limits of the control action respectively, can be described by:

$$u = sat(\hat{u}) = \begin{cases} u_{min} & \text{if } \hat{u} < u_{min}. \\ \hat{u} & \text{if } u_{min} < \hat{u} < u_{max}. \\ u_{max} & \text{if } \hat{u} > u_{max}. \end{cases} \tag{4.11}$$

4.2 Problems due to Variable Delay Time

We have already described in chapter 2 the reason of having a variable delay time in the pulp bleaching process; this is due to the variability of the inlet and the outlet pulp flow inside the bleaching tower. One main problem occurs in case of introducing an uncertainty in the variable delay time which affects the bleaching process closed loop performance and

stability. Figure 4.3 from [6] presents the peroxide dosage (top plot) and the pulp bleaching output (bottom plot) coming from controlling the pulp bleaching process using a model with fixed parameters and a model predictive control algorithm (DMC) as a controller. A variable delay time of 550 minutes in depicted in the output of the process. Once a $\pm 5\%$ uncertainty in the variable delay time is applied, the brightness response starts to show some "*blips*" at 500 minute intervals. In order to explain those blips, let us consider the -5% case, in which the brightness response occurs earlier than was expected. This implies that the early measurement of the brightness will cause an error in the estimation of the free response in the DMC control algorithm as was described in equation (4.5). Consequently, the future error between the predicted free response and the set point profile will no longer be zero, which causes a downward blip in the control action as time elapses. This will cause a blip in the brightness response after some delay time that will result in another error, and the story is repeated every delay time, resulting in peaking. In other words, if the measured brightness happened earlier than estimated, so it is considered as a positive disturbance added to the estimated brightness (*increase in the free response F*) which means that DMC will detect a new brightness (*positive disturbance*), thus will order the peroxide to decrease its amount starting from this time to the time the final estimated brightness is reached (*predicted*). This is why we get a downward blip. To understand deeply this problem, let us now explain those blips phenomena or those adverse transients from the physical and mathematical point of view.

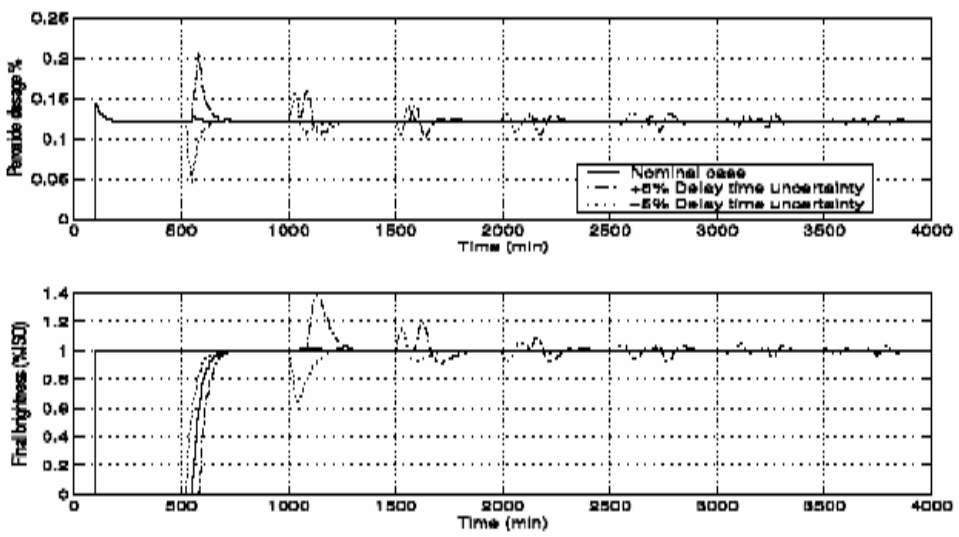

Figure 5.7: The system response to ∓5% delay time uncertainty.

Figure 4.3: The system response for ∓ 5 delay time uncertainty

4.2.1 Physical point of view

1. *Case* **of *early* real brightness (measured)**

   If the measured brightness responses earlier than estimated, then this is considered to be a positive disturbance added to the estimated brightness (**increase in the free response F**). This assumed disturbance causes the DMC algorithm to decrease the peroxide dosage at this time to reach the final desired brightness. This negative blip in peroxide dosage results in a blip in brightness after the process time delay.

2. *Case* **of *late* real brightness (measured)**

   If the measured brightness responses later than estimated, then this is considered to be a negative disturbance subtracted from the estimated brightness (**decrease in the free response F**). This assumed disturbance which causes the DMC algorithm to increase the peroxide dosage at this time to reach the final desired brightness. This overblip in peroxide dosage results in a blip in brightness after the process time delay. The illustration is shown in figure 4.4.

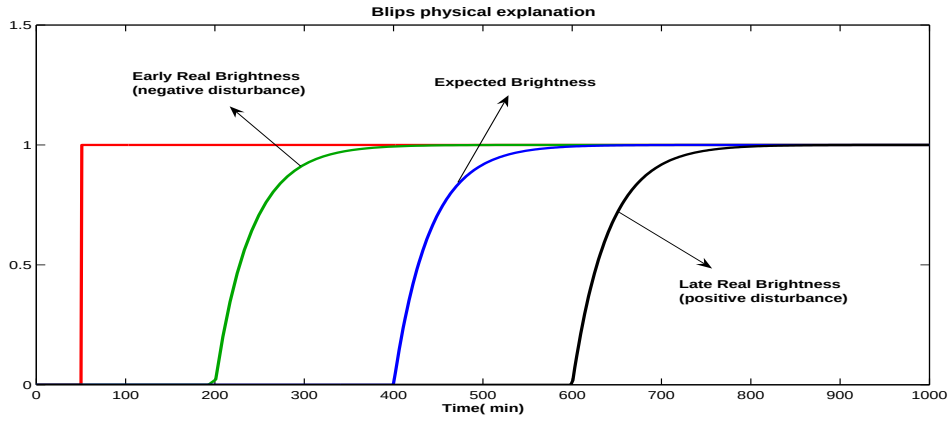

Figure 4.4: Physical explanation of blips

4.2.2 Mathematical point of view

1. **+5 % T_d Estimation Error**

   This case is illustrated in figure 4.5, where the real delay time is longer than the one estimated ($T_d(real) > T_d(estimated)$). Thus the free response **F** in this figure (F_1, F_2, ..., F_{N_p}) will respond after the reference trajectory ω (W_1, W_2, ..., W_{N_p}), so the error ($\mathbf{e} = \omega - \mathbf{F}$) is positive and then the control action $\triangle u$ will increase (starting from $T_d(estimated)$ to $T_d(real)$). In other words, in case of late response of

the final brightness, and referring to the free response in equation (4.5) where y_m is the measured output brightness, y_m decreases and so does F, yields to an increase in the error and then in the control action $\triangle u$ (**positive blips**).

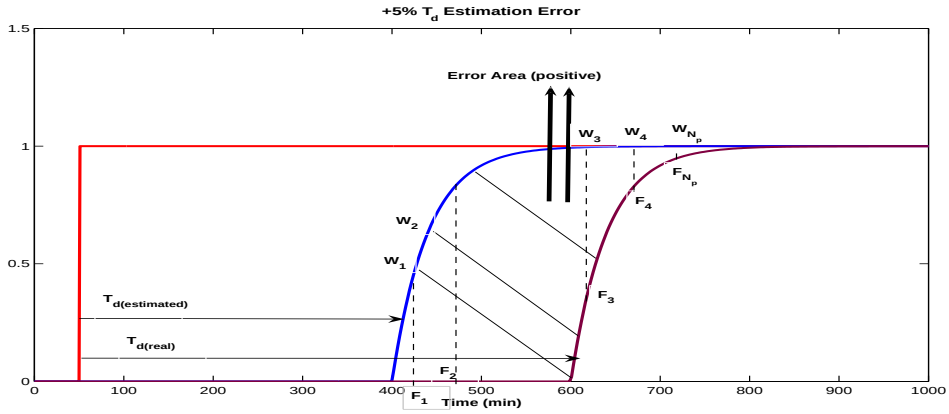

Figure 4.5: +5 % delay time estimator error

2. **-5 % T_d Estimation Error**

   This case is illustrated in figure 4.6, where the real delay time is less than the one estimated ($T_d(real) < T_d(estimated)$). Thus the free response **F** in this figure (F_1, F_2, ..., F_{N_p}) will respond before the reference trajectory ω (W_1, W_2, ..., W_{N_p}), so the error ($\mathbf{e} = \omega - \mathbf{F}$) is negative thus the control action $\triangle u$ will decrease (starting from $T_d(real)$ to $T_d(estimated)$). In other words, in case of early response of the final brightness, the free response in equation (4.5)where y_m is the measured output brightness, y_m increases and so does F, yields to an decrease in the error and then in the control action $\triangle u$ (**negative blips**).

4.3 Delay Time Predictor

We mentioned that the problem in figure 4.3 is due to the uncertainty of the variable delay time estimator. The symptom of this is the existence of transient spikes *blips* in the bleach dosage and unwanted variation in pulp brightness. We are suggesting a new approach, namely as *Smart Delay Time Predictor* which corrects the delay time uncertainty in the final pulp brightness as follows: Assume a brightness setpoint change is required at time t_o and a recommended control action (hydrogen peroxide dosage) is then brought into

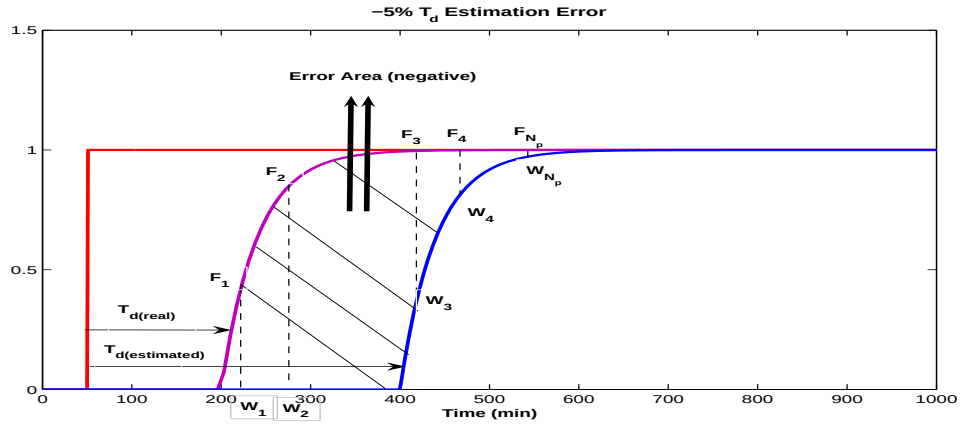

Figure 4.6: -5 % delay time estimator error

action to achieve the required pulp brightness. At this time the delay time is estimated ti be $\hat{T}_d^o$, i.e., the DMC algorithm "expects" that the brightness will respond at $t_o + \hat{T}_d^o$. As the time advances we continue to predict the exact delay time after which the output brightness should begin to track the set point, based on the inlet pulp flow and the variable level data, then advancing the delay time inside the MPC controller, step by step from $\hat{T}_d^1$ *to* $\hat{T}_d^k$, where k is the number of step prediction, and at the same time integrating the delay time backwards to a point where $\hat{T}_d^k$ equals the time back to the application of the step change. The difference of this type calculation compared to the one employed in [6] is that in [6] the delay time was calculated outside the DMC controller then stored as data and embedded inside the controller afterwards. But in our method, we calculate the delay time and then correct the controller inside the same loop of delay time calculation, then once the backward integration of the variable time delay reaches any setpoint change, the delay time calculation stops.

This method is valid for both cases of estimated delay time: either the response happens earlier than predicted or later than predicted. At that time, we predict correctly the delay time starting from the control action $\triangle u$ had increased till the start of the pulp brightness output to track the set point. Consequently, there is need to increase or decrease the *hydrogen peroxide dosage*. The illustration is shown in figure 4.7, where two types of time delay uncertainty (early and late respectively) are exhibited. Several arrows pointing backwards show the calculation method of the delay time predictor. As a conclusion, this novel time delay calculation method is presented to tackle the problem of adverse transients occurring in case of the uncertainty of the variable time delay, i.e., it eliminates transient spikes occurring during any miscalculation of the time delay inside the controller.

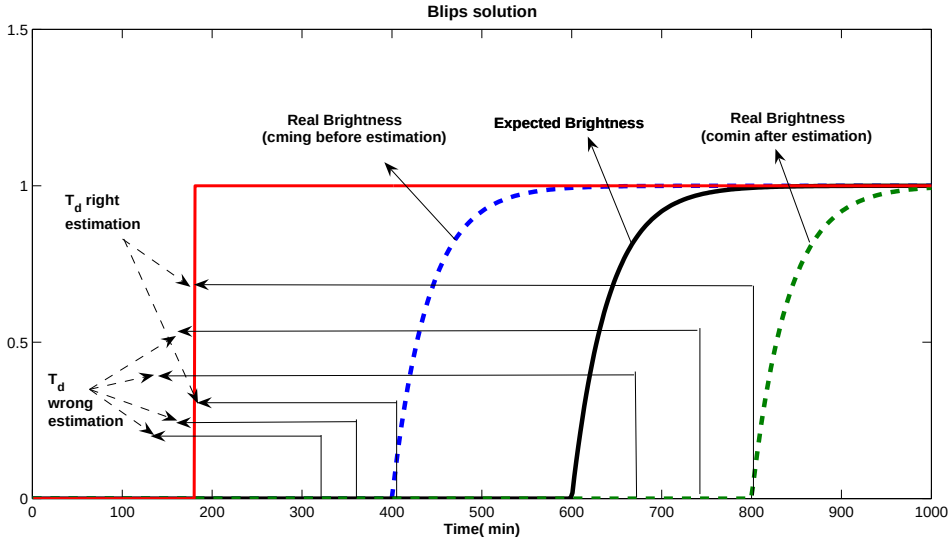

Figure 4.7: Solution for the blip problem

4.4 The indirect adaptive predictive control design for the bleaching process

We introduced in chapter 3 that an adaptive controller is a controller with adjustable parameters, which is tuned online according to some mechanism in order to cope with time-variations in process dynamics and changes in the environment. The outer loop constituted by the blocks in figure 3.2 denoted "identification" and "controller design" is what separates the adaptive controller from a conventional one. The identification block contains a recursive estimation algorithm which aims at determining the best model of the process at the current instant. The design block then applies this model to produce a model predictive controller strategy.

Figure 4.8 illustrates the Simulink model that was used to simulate the indirect adaptive predictive control closed loop system. The plant for the purpose of simulation was chosen as a first order discrete transfer function as previously mentioned in chapter 2. In this case, the bleaching process is handled as a SISO process. A simulation is illustrated in figure 4.10 and 4.11, where an indirect adaptive DMC controller with a delay time predictor is applied to control the pulp brightness, with the controller parameters, i.e. the prediction horizon $Np(k) = 4\tau + T_d(k)$ where τ is the bleaching process time constant, and the control horizon $Nu = 1$. The DMC control law presented in section 4.1.2 is simulated by using S-function under the Simulink. We implemented this S-function in an M-file to estimate

the unknown process parameters, to calculate the controller parameters and to implement the control law. Given the degree of the polynomials of the process model and the reference model parameters, the system will be simulated automatically. Notice that because of the phase delay of 200 samples in the beginning of the simulation, and due to the rise time of the model parameters till reaching stability (another 100 samples), we have to ensure that in the first 300 samples the real process parameters are set in the controller (using a clock as shown in the simulink model), then we switch the model parameters calculation to the RLS estimator. Otherwise, the controller will not be able to detect the model parameters because their initial values are set to zero when we start applying the RLS algorithm, yielding to an error in the controller S-function.

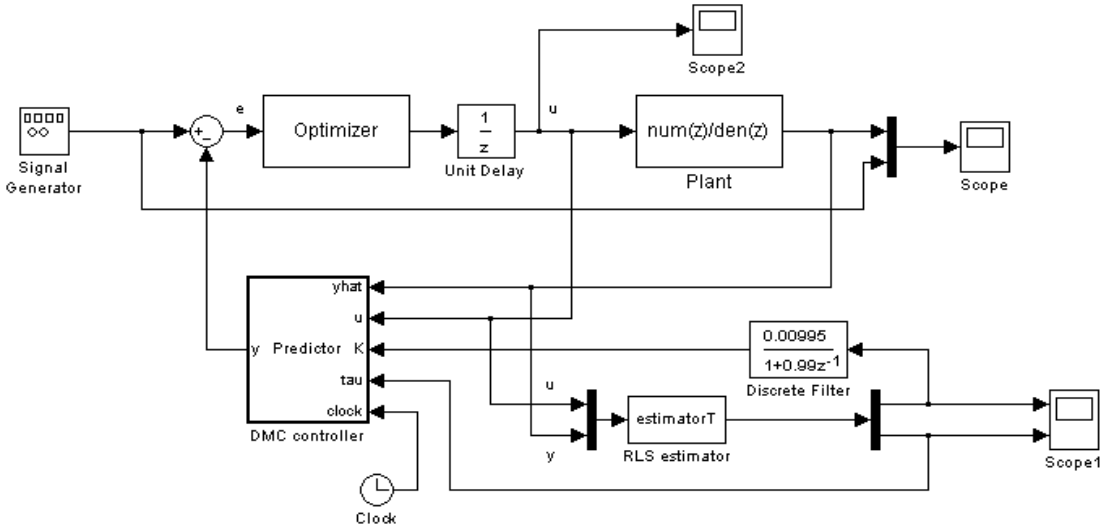

Figure 4.8: Simulink model of the indirect adaptive predictive control

The results without RLS gain filtering show a small downward blip in both the peroxide dosage and the pulp brightness. This is due to the setpoint changes that cause the gain and the time constant of the RLS model to change slightly at each setpoint change (see figure 3.6). The slight variation in the gain parameter which tend to recover after a short time constant is exhibited in figure 4.9. To solve such a problem, we include a discrete filter block that implements a finite impulse response (FIR) filter. We specify the coefficients of the numerator and denominator polynomials in ascending powers of z^{-1} as vectors using the numerator and denominator parameters. In this case, we assume a filter of numerator equal to 0.00995 and a denominator of 0.99, both are in the z-domain. The results are significant: There are no downward or upward blips either in the peroxide dosage or in the

final pulp brightness for the case of gain filtering in figure 4.10.

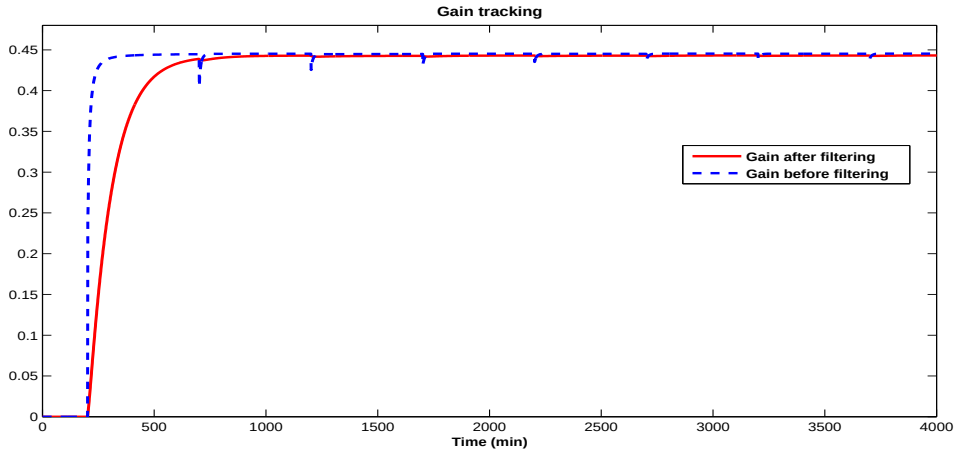

Figure 4.9: RLS gain estimator before and after filtering

the control action, due to the application of a square wave (a train of 0's and 1's setpoints) of different pulse widths occurring at different levels of the variable delay time, is shown in figure 4.10 in the *top plot*, whereas the final pulp brightness that tracks exactly the setpoint brightness signals after the delay time is in the *bottom plot*. The variable delay time in this scenario is shown in figure 4.11.

4.4.1 Robustness behavior

Using an online parameter estimation algorithm to identify the parameters of the model, the parameters of most linear model based controllers can be adjusted in line with changes in process characteristics. Although great strides have been made in resolving the implementation issues of adaptive systems, for one reason or other, many practitioners are still not confident about the long term integrity of the adaptive mechanism. This concern has led to another contemporary topic in modern control engineering; robust control.

Robust control involves, firstly, quantifying the uncertainties or errors in a "nominal" process model, due to nonlinear or time-varying process behavior for example. If this can be accomplished, we essentially have a description of the process under all possible operating conditions. The next stage involves the design of a controller that will maintain stability as well as achieve specified performance over this range of operating conditions. A controller with this property is said to be "robust" [34]. A sensitive controller is required to achieve

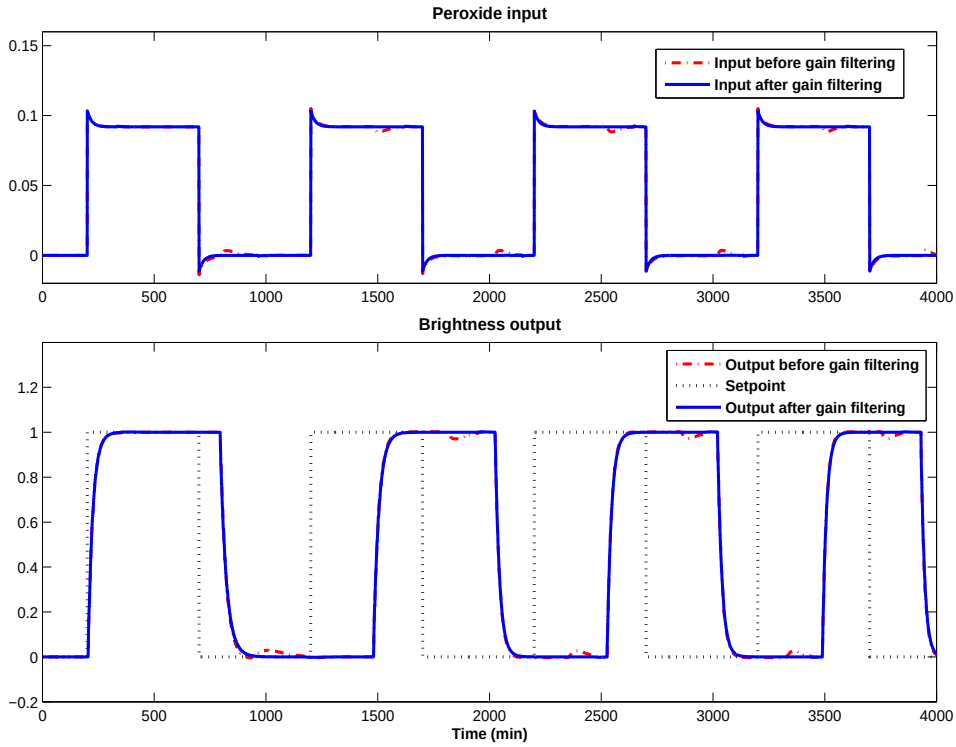

Figure 4.10: Input and output of the indirect adaptive predictive control before and after filtering

performance objectives. Unfortunately, such a controller will also be sensitive to process uncertainties and hence suffers from stability problems. On the other hand, a controller that is insensitive to process uncertainties will have poorer performance characteristics in that controlled responses will be sluggish. The robust control problem is therefore formulated as a compromise between achieving performance and ensuring stability under assumed process uncertainties.

In the previous section, we used S-functions to implement the indirect adaptive predictive algorithm, and we showed that the adaptive control can be very effective and can give good closed-loop performance. It is attributed to the adaptive behavior of the controller that it changes its parameters, not the structure, according to the changing dynamics of the system. However, that does not mean that adaptive control is the universal tool that should always be used.

The following simulations are intended to study the system behavior in the presence of parameter uncertainties in the pulp bleaching process. To corroborate the robustness results instead of using as a control model the linear model that best fits the nonlinear process,

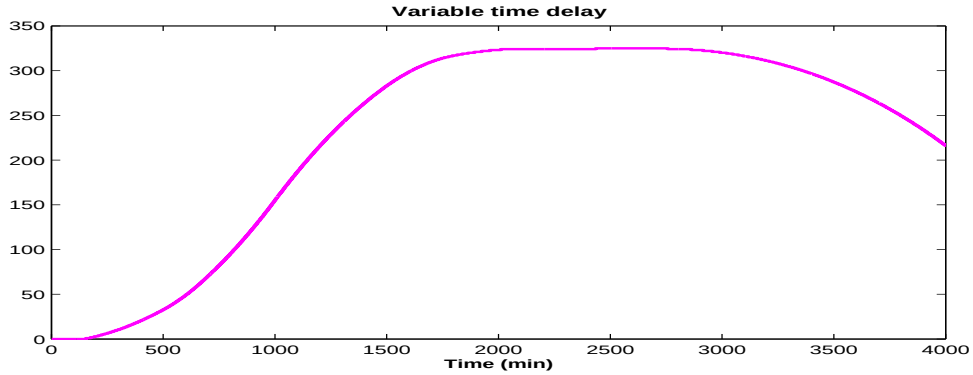

Figure 4.11: Variable delay time

a model with estimation errors is used. For example, when working in a model with a error of ±25% on the gain, thus we recalculate the control action for those new values, the response of shown in figure 4.12 is obtained, where an additional input dosage is added to accommodate the amount of gain uncertainty. The final pulp brightness responses (+25% as the dotted line and -25% as the dash-dotted line in the *bottom trace*) differ from the nominal case by not tracking the setpoint for a quite a long time, equal to the previous delay time. Fortunately, it correct itself after that. That shows that our DMC controller is robust despite the big percentage gain uncertainty.

Another robustness behavior is presented in figure 4.13 where the model is subjected to a ±25% time constant uncertainty. The simulation depicts small transients in the multivariable input and the controller output after an additional process delay time. That shows that a perturbation in the bleaching process time constant has only a minor effect on the input and output responses.

4.5 Multivariable MPC

Most industrial plants have many variables to be controlled (*outputs*) and many manipulated variables used to control the plant (*inputs*). In some cases a change in one of the manipulated variables generally affects the corresponding controlled variable and each of the input-output pairs can be considered as a single-input single-output (SISO) plant and controlled by independent or decoupled loops. In several cases, when one of the manipulated variables is changed, it not only affects the corresponding controlled variable but also perturb the other controlled variables. These interactions between process variables

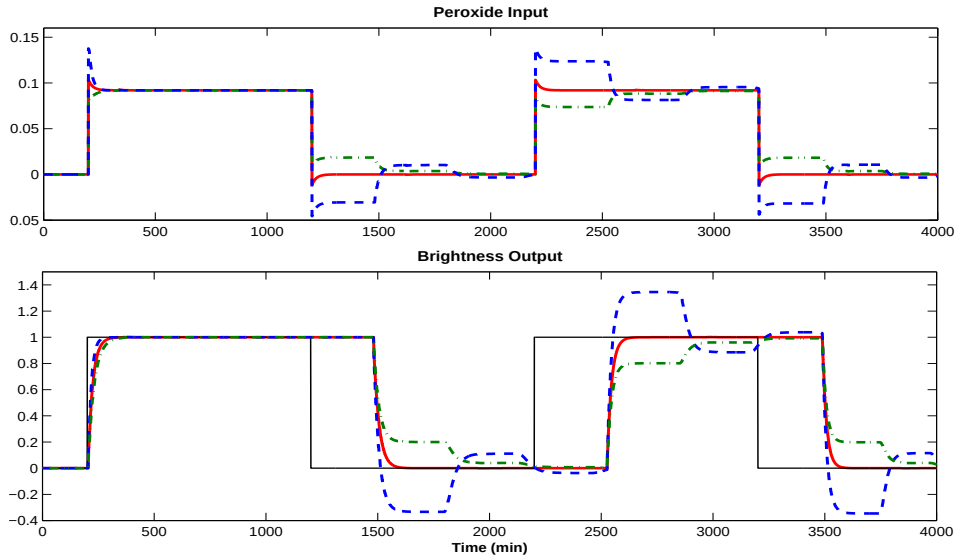

Figure 4.12: Robustness behavior for ±25% gain uncertainty

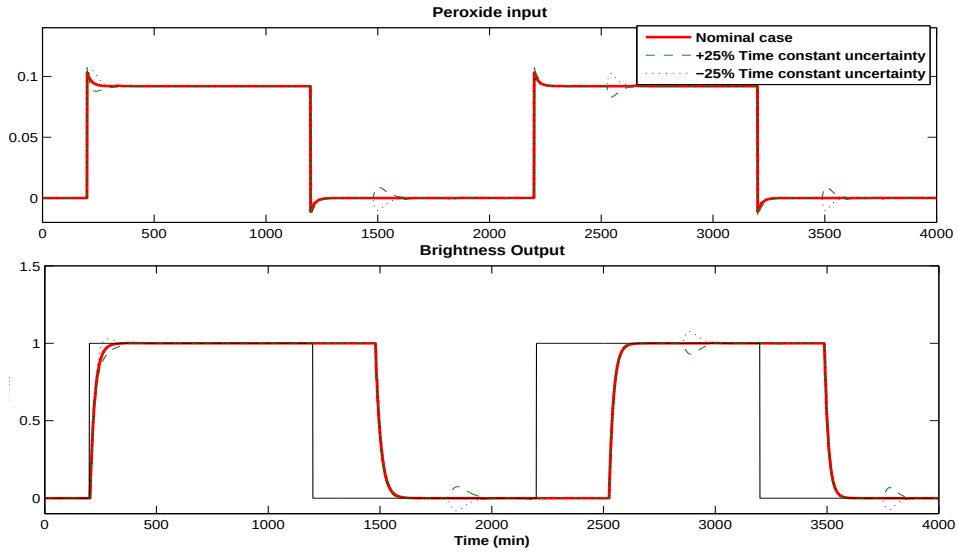

Figure 4.13: Robustness behavior for ±25% time constant uncertainty

may result in poor performance of the control process and even instability. When the influences are not negligible, the plant must be considered to be a process with multiple-inputs multiple-outputs (MIMO) instead of a set of of SISO processes. In our study of the mechanical pulp process, we consider the manipulated variables as the *hydrogen peroxide* H_2O_2 and the *sulfur dioxide* SO_2. The controlled variables are scrutinized as the *pulp brightness output* and the pH. Total decoupling is very difficult to achieve for such a process which exhibit complex dynamics and varying dead times.

Bleaching applications are some of the toughest pH measurement challenges in process industry. They nearly always expose the sensors to high pressures, high temperatures, high solids, and rapidly changing chemical compositions. Installation of pH probes is also difficult due to the high velocity and pressure of the process. Also, because the pulp lines are so large, often 24 inches in diameter, it is difficult to ensure that the pH probe is inserted into the area of flow that provides a representative measurement. Selection of wetted sensor materials is also a concern. The chemicals used in bleaching are aggressive, and with high temperatures will attack many metals and plastics. Good pH control is extremely difficult due to the continuous nature of the process. Often, the process is simply moving so fast that there is insufficient retention time for the pH to stabilize, thus the pH may still be changing at the hydrogen peroxide (H_2O_2) injection point. Because this control is related to brightness, a stable pH value is desired, but not always achievable. To maintain good pH control, temperature swings must be avoided. Therefore, one of the most important variables affecting the pulp quality is the pH at the end of the stage, i.e. at the exit of the first caustic extraction tower [35]. The target pH after the tower is usually between 4 to 4.5. Low pH degrades the pulp quality and increase chemical consumption in further bleaching stages. High pH proves to be of no substantial benefit while the additional caustic consumption is costly. Thus, it is desirable to minimize caustic consumption while maintaining pulp quality. A good control scheme will allow lowering the pH target while maintaining the pulp quality and minimize the caustic consumption. The control problem is complicated by the fact that the buffering effect provided by the aqueous system may vary, and by the time-varying nature of the dynamics. The MIMO controller is not studied here because of the lack of knowledge on the factors affecting the pH model identification such as $NaOH$. That will yield to inaccurate control response.

Chapter 5

Conclusions

1. The mechanical pulp bleaching process at *Irving Paper mill* has been described, analyzed and modeled. Hydrogen peroxide dosage, SO_2 dosage, incoming pulp brightness, and pulp consistency are considered the most crucial factors affecting the bleaching process output considered here: the pulp brightness output and pH. Hydrogen peroxide H_2O_2 and SO_2 are taken as the inputs.

2. An important class of systems in the process industry deals with material transport, in which the liquid flow rates and volumes may be continuously varying. Often it is possible to describe these kinds of systems with linear models, in which the parameters are variable. The result is an extension to cover continuously varying operation conditions, viz. the case of varying flow rates in a material transport process. Also, the case with varying volumes has been discussed, and the related problems in this case have clearly been revealed by the developed mathematical methodology.

3. The discussion was then extended to cover time delays, which are naturally modeled by using plug flow vessels. The concept of the variable delay time was introduced, analyzed and illustrated through descriptive figures for both cases: the delay time based either on the inflow or the outflow.

4. A thorough explanation of the modeling of the pulp bleaching process using three offline and online identification algorithms, with full descriptions and simulations, was considered yielding to impressive results for modeling the bleaching process. This work was a comparison and an extension of single-input single-output and multiple-input single-output system identification simulations employed in [6] bringing in sig-

nificant results.

5. A nonlinear time-varying process can be executed online (using online identification algorithms) by an indirect adaptive predictive controller (using model predictive control as a controller) was described and applied for a single-input single-output process where hydrogen peroxide and final pulp brightness are the process input and output respectively.

6. identification of the process has demonstrated the crucial SO_2 impact on both the pulp output brightness and the pulp pH. This will yield to the control of the pulp pH improves both the efficiency of the bleaching process and the quality of the produced paper. But, taking $NaoH$ into account while doing the identification will lead to better control results. This was beyond the scope of this thesis.

7. A novel time delay calculation method is presented that tackles the problem of adverse transients occurring in case of the uncertainty of the variable time delay, i.e., eliminates the transient spikes occurring due to miscalculation of the time delay inside the controller. The efficacy and robustness of this technique is demonstrated by controlling the pulp bleaching process using a model predictive control (MPC) algorithm with a variable delay time embedded in that controller. The contributions of this method presented here include the delay time predictor that: (1) is straightforward to implement and to use (2) corrects the uncertainty of the delay time estimator, and (3) is reliable for a broad class of chemical process.

8. Drawbacks of PID controllers with time-varying systems were discussed. An indirect adaptive model predictive controller design method for a $SISO$ model using RLS estimator was then developed to demonstrate the practical applicability of the theory. A filter was added to the gain parameter estimator to suppress the spikes due to transients in identified parameters with each change in the setpoint. The stability and robustness of the closed loop system was shown to be a direct consequence of the design method. The controller exhibits a good response to changes in both gain and time constant model parameters. These contributions have produced an effective solution to a difficult control problem.

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Appendix IV

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