INDIRECT ADAPTIVE MODEL PREDICTIVE CONTROL OF A MECHANICAL PULP BLEACHING PROCESS

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ABSTRACT
The classic way to control a process, in a model based framework, is to obtain a model of the system and then use it for the design of a controller. A time-varying process can require use of a real-time indirect adaptive controller, and a process with variable time delay may also call for a delay-time predictor. This paper describes a particular structure for such a controller and demonstrates its application to a pulp bleaching process. The variable delay time predictor constitutes the novel contribution of theis work.

We discuss aspects of controlling the pulp bleaching process at Irving Paper Ltd., which is an extension on the work done in Sayda and Taylor [1]. The bleaching process was thoroughly studied, and single-input single-output process models identified on-line. This investigation showed that 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 substantially with pulp flow into and out of the bleaching vessel. The efficacy and robustness of our new technique is demonstrated by controlling the pulp bleaching process using an indirect adaptive model predictive control algorithm with a recursive least squares identifier and a variable delay time predictor embedded in that controller.

KEY WORDS
Indirect adaptive control, predictive control, on-line identification, pulp bleaching process, variable time delay.

1 Introduction

Process industries need a predictive controller that is low cost, easy to setup and maintains an adaptive behavior which accounts for time-varying dynamics as well as potential plant mismodeling. To answer this need for the mechanical pulp bleaching process, we present the architecture of an indirect adaptive MPC scheme and study it as a single-input single-output (SISO) control system.

The classic way to control a system, in a model based framework, is to obtain a model of the system and then to use it for the design of a controller. Such a model can be obtained once off-line if the dynamics are not time-varying, or identified on-line if there is a need to adapt to time-varying dynamics. The latter choice was made for the architecture of our controller which, as result, is indirect and adaptive. For the identification part of the procedure a recursive least squares (RLS) on-line identification algorithm was applied.

The description of the plant to be controlled is introduced in Section 2, to serve as the basis for choice of a model structure for identification. Section 3 describes the identification algorithm employed to model the system. A brief introduction to adaptive control is given in Section 4, then an adaptive predictive controller is designed for the identified process model. Sections 5 and 6 present simulation results and conclusions, respectively.

2 Dynamics of Pulp Bleaching

Pulp is the primary raw material for making paper. Paper is made from fibers [2]. 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 active wood is slightly colored, whereas residual lignin remaining after an alkaline pulping process 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, wood is broken down into fibers with little or no lignin removal. The bleaching of pulp takes place by decolorization; bleaching to remove lignin not only increases the brightness but improves 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. Bleach plant technology is currently in a state of flux as a result of concern for the environmental impact of chemicals, such as chlorine. As a result, the industry is moving towards new chemicals, chiefly hydrogen peroxide, mainly called "peroxide" [3]. These chemicals are mixed with pulp suspensions and the mixture is retained at a prescribed pH, temperature and concentration for a specific period of time.

The industry standard when the brightness target does not exceeds 75% is the medium consistency single-stage peroxide bleach plant depicted in figure 1. Pulp is treated as follows: The bleaching of mechanical pulp with hydrogen peroxide is usually carried out by treating the pulp using DTPA or pentasodium diethylenetriaminepentaacetic, which is added to remove transitional metal ions in the pulp; 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. The objective of the caustic extraction stage (NaOH) is to remove the alkalisoluble portion of the lignin from the woodpulp. Finally, a small amount 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 to 10% of the amount applied is desirable. Most systems inject sulfur dioxide SO_2 at the outlet of the retention tank to prevent reversion and for pH adjustment. After this processing, three steps are generally required: (a) washing of the bleached pulp, (b) heating to the desired temperature, and (c) retention to complete the reaction. This modification in the refiner mechanical pulp process is called thermo-mechanical pulping.

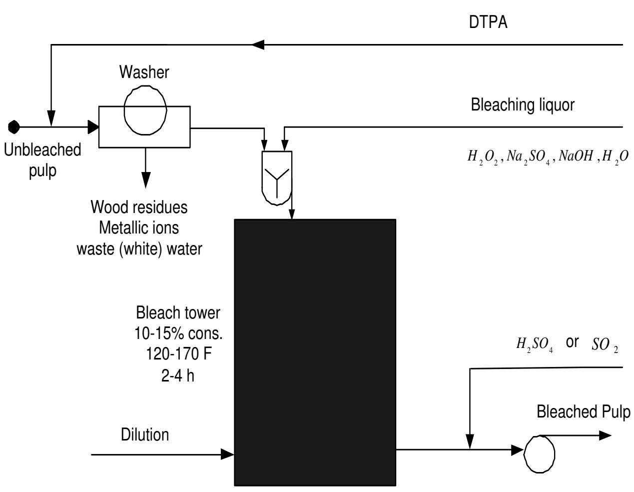

Figure 1. Single-stage peroxide bleaching flowsheet [2]

3 On-line Model Identification

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 retention tower can be treated as a continuous stirred tank reactor (CSTR) followed by a plug flow reactor (PFR). The part of the process where the material is mixed can be modeled as a first-order lag, $K\,/\,(1 + s\tau)$. One may model plug flow, in which the process material is assumed to flow without any mixing occurring, as a pure time delay or transport, e^{-sT_d}.

Fluid-dynamic systems are inherently nonlinear and are subject to a combination of coherent and random unsteady disturbances. As a result, accurate low-order analytic models are difficult to obtain for real-time control of such systems. Therefore, controllers implementing adaptive on-line system identification are ideally suited to flow control problems [4]. Since the system is time-varying, we use the recursive least squares (RLS) algorithm with exponential forgetting to track the variation in the model. A modified RLS procedure is used at each time step to obtain the parameter vector together with the covariance matrix $P(k)$. To correctly estimate the varying model parameters the assumption must be made that their rate of change is substantially slower than the sampling time. The exponential forgetting factor λ (i.e., a decay weight $0 < \lambda < 1$) is applied to the measured data sets (e.g., heavy weighting is assigned to the most recent data due to its importance, versus a small weight in the case of older data). The core of the RLS algorithm is thus the update of the covariance matrix:

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

where

$$L(k) = P(k-1)\phi(k)(\lambda + \phi^T(k)P(k-1)\phi(k))^{-1} \qquad (2)$$

is the Kalman gain used to update the previous estimate based on new measurement data. Finally the model parameter vector estimate $\theta(k)$ is obtained by adding a correction to the previous estimate. The correction is proportional to the difference between the real output of the plant or disturbance and its prediction based on the previous parameter estimate:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + L(k)(y(k) - \phi^T(k)\hat{\theta}(k-1)) \qquad (3)$$

where $y(k)$ and $\phi(k)$ are the actual data vector and the regression vector respectively. Typical values for these parameters used inside the controller are $P(0) = 10^5 I$ and $\lambda = 0.999$.

4 Controller Design

4.1 Indirect Adaptive Predictive Control

In every language, to *adapt* means to change a behavior to conform 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. As a special case, an adaptive controller is a controller with adjustable parameters and a mechanism to adjust the parameters; it is a nonlinear controller, due to the parameter adjustment mechanism. Such an adaptive controller tunes its own parameters or otherwise modifies its control laws so as to accommodate fundamental changes in the behavior of the process [5].

Hundreds of techniques for adaptive control have been developed for a wide variety of academic, military, and industrial applications. Arguably, the first rudimentary adaptive control scheme was implemented by Kalman in the late 1950s using a custom-built analog computer [6]. The term self-tuning regulator was coined by Åström who gave the first analysis of the steady-state properties of self-tuning regulators based on minimum variance control [7]. The stability of the closed-loop system and the convergence properties were analyzed in [8]. More details of the properties of self-tuning regulators and adaptive controllers can be found in [9, 10].

An adaptive control system can be thought as having two loops as exhibited in figure 2. The inner loop consists of 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 calculation, where the controller design represents an on-line solution to a design problem for a system with known parameters; the controller parameters are obtained from the control design problem solution.

The model predictive control (MPC) scheme, discussed below, is very flexible with respect to the choice of the underlying design and estimation methods. For time-invariant systems 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. The self-tuning regulators are thus a special class of adaptive controllers.

4.2 Model Predictive Control

Model predictive control (MPC) refers to a class of algorithms that compute a sequence of manipulated variable (process input) adjustments in order to optimize the future behavior of a plant. Originally developed in the process industries in the 1960s and 70s, based primarily on heuristic ideas and input-output step and impulse response models proposed by Richalet *et al* in 1976 and then summarized in a 1978 Automatica paper [11], MPC technology can now be found in a wide variety of application areas including chemicals, food processing, automotive, aerospace, metallurgy and pulp and paper [12].

The basic principle of MPC is to solve an open-loop optimal control problem at each time step. The

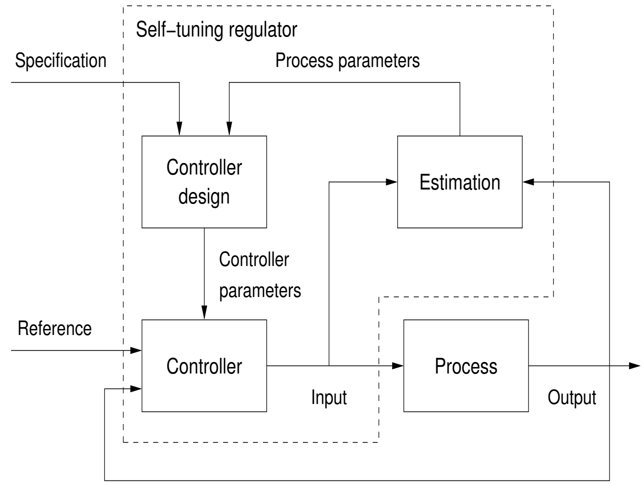

Figure 2. Indirect self-tuning regulator [9].

decision variables are a set of future manipulated variable moves, and the optimization objective is to minimize deviations from a desired trajectory; constraints on manipulated, state and output variables can be handled naturally in this formulation. Feedback and adaptation are achieved 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 [13].

The concept of predictive control involves the repeated optimization of a performance criterion, eqn. (4), over a finite horizon extending from the next future time step up to a prediction horizon N_p steps ahead. Two terms are traded off, the sum of the squared error or difference between the predicted process output $\hat{y}$ and a reference signal w, and the sum of the squares of the control moves:

$$J = \sum_{j=1}^{N_p} [\hat{y}(t+j|t) - w(t+j)]^2 + \sum_{j=1}^{N_u} \mu [\Delta u(t+j-1)]^2 \quad (4)$$

where μ is a positive constant that can be used to tune the MPC controller to achieve the required performance. The minimization is performed subject to constraints on the input level, of the form

$$u = \mathrm{sat}(\hat{u}) = \begin{cases} u_{min} & \text{if } \hat{u} < u_{min}. \\ \hat{u} & \text{if } u_{min} < \hat{u} < u_{max}. \\ u_{max} & \text{if } \hat{u} > u_{max}. \end{cases} \quad (5)$$

For prediction it is assumed that $\Delta u(t+j) = 0$ for $j > N_u$. Manipulating the control $u(t+j)$ over the control horizon N_u, the algorithm drives the predicted output $\hat{y}(t+j)$, over the prediction horizon, towards the reference $w(t+j)$, which is the desired setpoint or a close approximation to it. In our study, a smooth reference signal $w(t+j)$ is produced by filtering: Given a desired setpoint $s(t+j)$, $j = 1 \dots N_p$,

$$w(t+j) = \alpha\, w(t+j-1) + (1-\alpha) s(t+j)\,, \; j = 1 \dots N_p \quad (6)$$

where α is a parameter between 0 and 1 (the closer to 1, the smoother the approximation) that constitutes an adjustable value that will influence the dynamic response of the system, and $s(t+j)$ is the constant future reference or setpoint. In our application, constraints are not managed through optimization but by using an anti-windup scheme, since it has been shown to have performance quite similar to that of constrained MPC.

4.3 Delay-time Predictive Control

We use an indirect adaptive dynamic matrix control (DMC) scheme. This approach to MPC uses step response data generated from the internal model $Ke^{-sT_d} / (1+s\tau)$. In essence, when a set-point change ΔS is given the DMC controller "expects" a response $\hat{T}_d$ sec. later, of the form $\Delta S(1 - e^{-(t-\hat{T}_d)/\tau})$. If the actual response occurs later than expected, then the DMC algorithm will produce an additional Δu and the process will experience a positive transient T_d sec. after that (a positive "blip"), or if the actual response occurs earlier than expected it is treated as a disturbance to be rejected by the DMC controller; a negative Δu is produced and thus a negative blip occurs.

This problem was solved by a novel strategy presented in [14]. The basic idea is that by continually monitoring the flow out of the bleach tower from the instant the set-point change occurs one can continually estimate (predict) when the process response will happen, and that prediction will be exact at the moment the response does occur. If the DMC controller uses this estimate, then blips will not exist, as demonstrated in [14].

5 Simulation Results

Figure 3 illustrates the Simulink model that was used to simulate the closed loop system with indirect adaptive predictive control. The plant for the purpose of simulation was chosen as a first-order discrete transfer function, as previously mentioned in Section 2. In this case, the bleaching process is handled as a SISO process. The controller parameters include the prediction horizon, $N_p(k) = 4\tau + T_d(k)$ where τ is the bleaching process time constant and $T_d(k)$ is the variable time delay associated with plug flow, and the control horizon, $N_u = 1$. The MPC control law presented in Section 4 is simulated using an S-function in 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. Notice that due to the time offset of 200 samples before the first set-point change at the beginning of the simulation plus the rise time of the RLS model parameter estimates before reaching steady state (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 to those provided by 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.

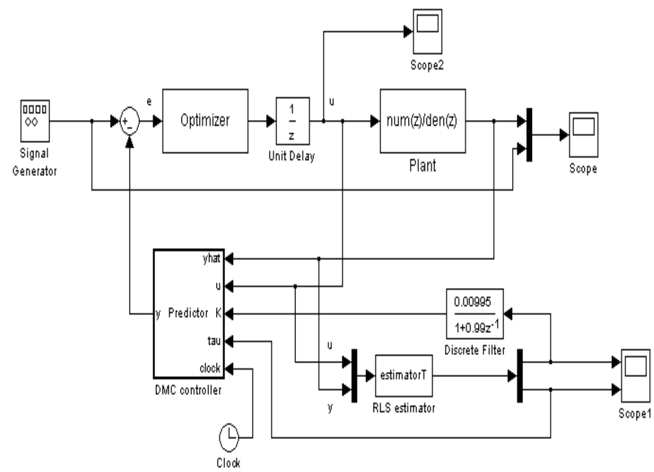

Figure 3. Simulink model of the indirect adaptive predictive control

5.1 Nominal Behavior

A typical simulation result is portrayed in figures 4 and 5, where an indirect adaptive DMC scheme with a delay-time predictor is applied to control the pulp brightness. First, we focus on the RLS estimator behavior: The results without RLS gain filtering, as depicted in the dashed line in figure 4, show a small downward "blip" at each set-point change (every 500 samples), due to the transient response of the RLS algorithm. To solve this problem, we included a discrete filter block, as shown in the simulink model, 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; here we assume a filter of numerator equal to 0.00995 and a denominator of 0.99, both in the z-domain. The results are significant: There are no blips either in the peroxide dosage or in the final pulp brightness for the case of gain filtering, as shown in the solid line plots in figure 5.

Turning to the process behavior, figure 5, the control action (top plot, peroxide input), due to the application of a square wave set-point input (dashed curve, middle plot), is likewise periodic. However, the brightness response (solid curve, middle plot) is not periodic; rather, one can clearly see that the variable time delay (bottom plot) changes the initiation of the brightness changes and the duration of each change. The fact that there are no blips in brightness are due to the use of our delay-time predictor.

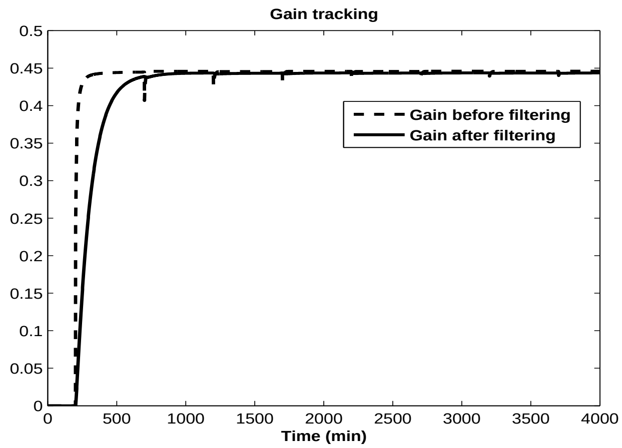

Figure 4. RLS gain estimator before and after FIR filtering

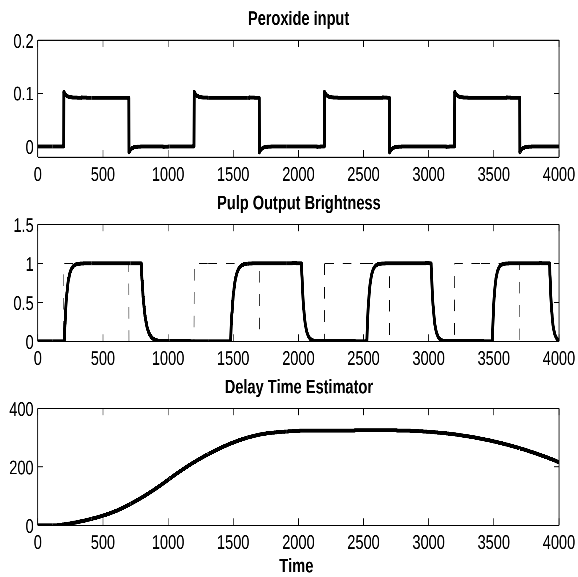

Figure 5. SISO process with predictor variable delay time

5.2 Robustness Behavior

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" [15].

In the previous section, we used S-functions to implement the indirect adaptive predictive algorithm, and we showed that it is effective and can give good closed-loop performance. This is attributed to the adaptive behavior of the controller due to the use of RLS gain estimation and the time-delay predictor to change its parameters to accommodate the changing dynamics of the system.

The following simulations illustrate the system behavior in the presence of parameter uncertainties in the pulp bleaching process. Instead of using as a control model the linear model that best fits the nonlinear process, a model with estimation errors is used. In one study we considered the effect of using an internal model with an error of $\pm 25\%$ in the RLS gain estimator, to calculate the control action; the response of shown in figure 6. 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; after an interval equal to the delay time the controller can adjust to a perceived disturbance and corrects itself after that. That shows that our MPC controller is robust in the sense of stability, despite the poor initial performance due to the large percentage gain uncertainty.

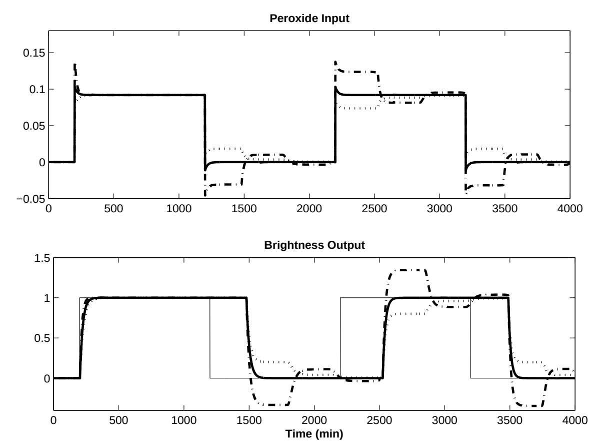

Figure 6. Robustness behavior for $\pm 25\%$ gain uncertainty

A second robustness test is presented in figure 7 where the model is subjected to a $\pm 25\%$ time constant uncertainty. The simulation depicts small transients in the manipulated 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.

6 Conclusion

A time-varying process has been successfully controlled by an indirect adaptive predictive controller

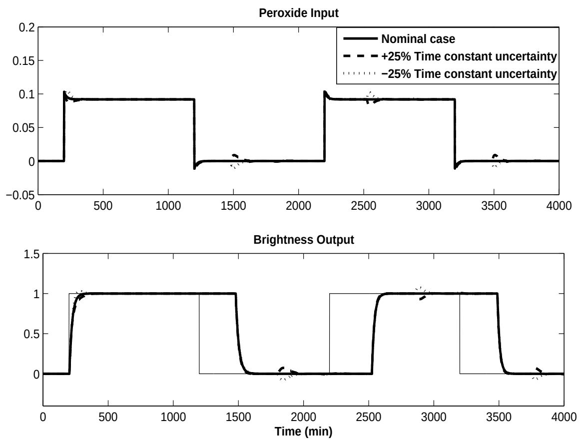

Figure 7. Robustness behavior for ±25% time constant uncertainty

based on model predictive control augmented by an on-line RLS identification algorithm and a delay-time predictor. This novel control system 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. The stability and robustness of the closed loop system was shown to be a direct consequence of the design method. The controller exhibited an acceptable response to changes in both gain and time constant model parameters.

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