ADAPTIVE PREDICTIVE NONLINEAR CONTROL - Part 3: Advanced Control Development, Simulation Testing, and Mill Performance

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ABSTRACT

This is the last of a 3 part series of papers published at the Control Systems '92 Conference at Whistler, B.C. describing the development of an advanced control application from concept to start-up. Recent advances in dynamic simulation, adaptive process control technologies and on-line analyzers provide the necessary environment to develop new approaches to complex control problems. This environment is described in the companion papers Part 1: The Tool-***High Fidelity Real-time Dynamic Process Simulation with Object Oriented Programming***, Part 2: The Model-***Fixed Time Zone Methodology for Plug Flow Simulations as Applied to an Oxygen Delignification Reactor.***

The resulting advanced control application presented here addresses the problem of tight Kappa control under disturbance conditions in an oxygen delignification reactor. With modification, similar techniques are applicable to continuous digesters, bleach plants and continuous reactors in other industries. Modern dynamic simulation tools, with high fidelity process models are used to develop a new adaptive, dead time compensating, predictive control strategy incorporating a nonlinear kinetic model. The unique aspect of this adaptive nonlinear control technique is its ability to accurately predict and control highly nonlinear processes and automatically learn and adapt to changing process conditions. Its key feature is the ability to compensate for any incorrect or changing model parameters providing for robust operation in real world environments. The strategy is easy to operate as it constantly checks itself for prediction accuracy via on-line kappa sensors. It can be implemented in almost any DCS thereby avoiding the need for external "black boxes". Mill trials to date show a reduction in outlet Kappa standard deviation compared to inlet Kappa standard deviation up to 65% depending upon the severity of the inlet Kappa disturbance. Tight Kappa control translates to more stable bleach plant operations, higher quality pulp, lower chemical costs and reduced environmental impact.

INTRODUCTION

Oxygen delignification provides an opportunity to lower Kappa targets to the bleach plant, thereby reducing bleaching chemical costs and environmental impact. Worldwide competitive pressures have also resulted in a trend toward tighter Kappa variation specifications for higher quality pulp. Yet, Kappa targets cannot be lowered to their optimal point without tight control over variations. Otherwise, excessive delignification could result during upsets reducing pulp quality.

Maintaining tight control of Kappa under all normal and upset process conditions requires an advanced control strategy that can deal effectively with the complex, changing process dynamics. Tight control is complicated because of the reactor's significant and varying dead time (retention time). Routine dead time fluctuations due to production rate changes, consistency variations and other process disturbances create a major challenge to any control strategy. The effect on outlet Kappa of inlet chemical and temperature changes cannot be measured until after a significant delay (retention time of 45 - 90 minutes or more). By then it is too late to correct for any Kappa target errors.

Precise control must consequently be based upon an accurate **prediction** of the resulting Kappa. Accurate prediction requires both knowledge of the process response characteristics and current process conditions.

Due to process complexities, use of Kappa sensors in a traditional PID control loop has severe limitations that must be overcome by more advanced control techniques.

his paper presents an innovative approach to predictive model based control. The paper is intended to provide basic understanding of the concepts incorporated for those without a control theory background. A minimal amount of state space description is included in the appendix for those so interested.

MODEL BASED CONTROL-BACKGROUND

Due to the complexities of the Kappa control process (multivariable, time variant, highly nonlinear reaction kinetics, and long, varying dead-times) some type of model based control is recommended for tight Kappa regulation. Often, model based control is supervisory. This means it is used in an outer cascade loop that calculates setpoints for inner loop PID controllers. Basically, the models are used to predict process response and make appropriate control adjustments based on those predictions. Typically, if the model generates accurate predictions, and maintains stability, the control will be very good.

The difficulty is developing an accurate model which will maintain its accuracy over time-varying operating conditions. Models can be linear or non-linear, fixed or adaptive. Fixed models have parameters that are "fixed" based upon initial, or average test data. (See Figure 1.) Adaptive models automatically adjust during operation to maintain model accuracy over time. Most successful applications of adaptive models to date have been linear. Most nonlinear models used in control are fixed due to the complexities traditionally inherent in adaptive nonlinear control.

An **adaptive linear** model is often used as an approximation of the nonlinearities. The adaptation mechanism attempts to generate a family of linear models by continuously adjusting parameters to approximate the nonlinearities. For highly nonlinear processes this is sometimes very difficult to accomplish as the adaptation mechanism can be strained to converge or remain stable under certain process conditions or highly nonlinear regions of the process.

The traditional alternative, a **fixed nonlinear** model, would typically require recalibration and retuning of parameters often on a highly nonlinear time-variant process.

ADAPTIVE NONLINEAR CONTROL

What is needed is a reliable approach to **adaptive nonlinear** models for highly nonlinear time-varying processes. In addition, embedded dead-time compensation is needed for processes with long and varying dead-time.

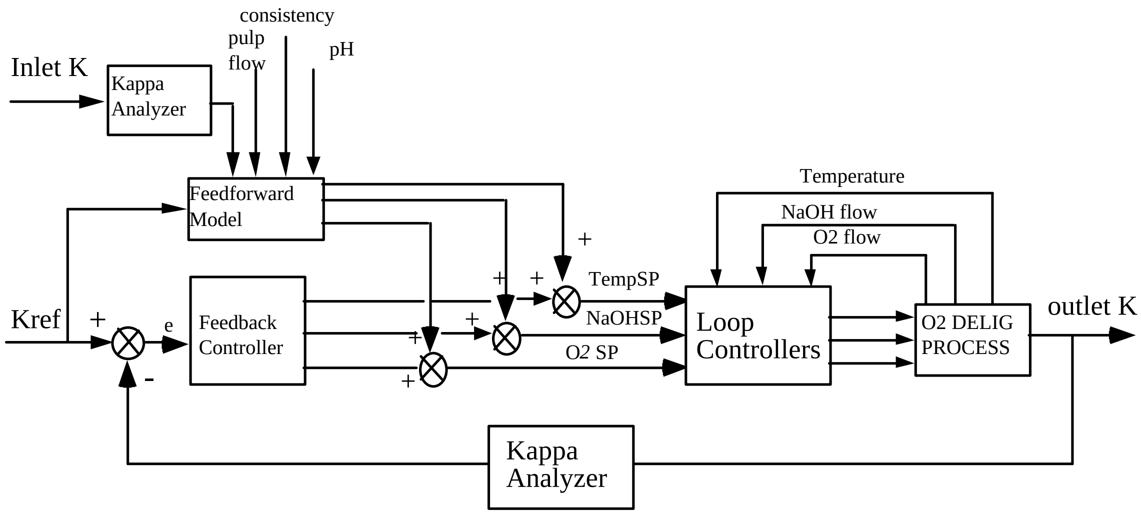

Figure 1. <u>FIXED</u> (Linear or Nonlinear) Model Based Control Strategy

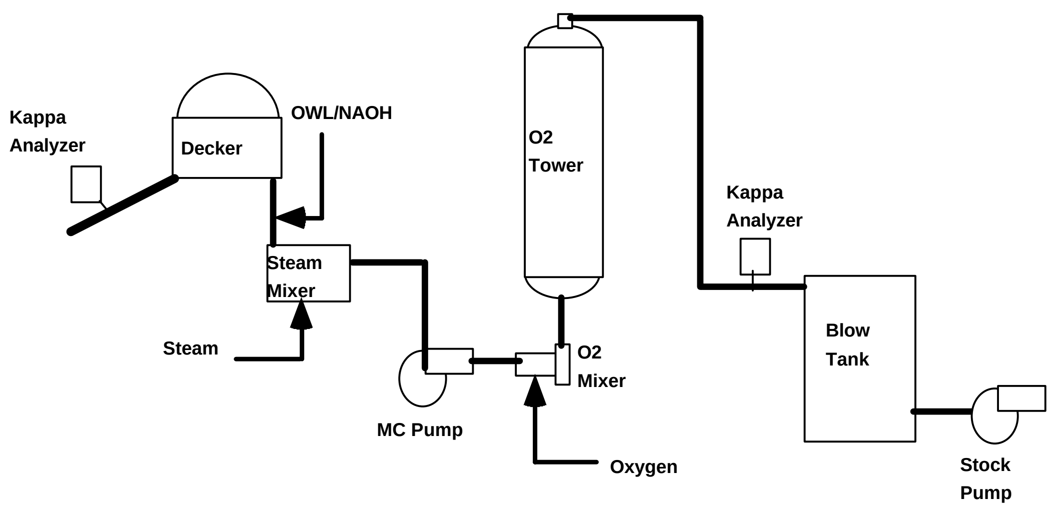

Figure 2. Oxygen Delignification Process.

This paper describes a new approach for developing model based control. It is both adaptive and non-linear plus variable dead time compensating. Its design objectives and a description of the resulting Advanced Control Package follow. Similar techniques can be applied to other nonlinear processes with significant dead time.

OBJECTIVE

Reliable, tight control of a complex chemical process that is nonlinear, time varying, multivariable, with large dead time.

Process Description

The oxygen delignification process is shown in Figure 2. Kappa measurements are taken both upstream and downstream of the reactor as shown. The continuous plug flow reactor's retention time will vary from 45 minutes to 90 minutes or more depending on its design and production rate. This means that off target Kappa outlet measurements taken now cannot be effected by adjusting inlet chemicals; it is too late. The required adjustment should have been made 45-90 minutes ago. Also the “correct” adjustment should have been made under whatever disturbance conditions existed, considering the interrelated effect on Kappa of all multivariables (time, temperature, oxygen, and caustic). Kinetics of the reaction complicate prediction of Kappa because studies have shown that observed response characteristics can be explained by assuming there are 3 categories of lignin; nonreactive, slow reacting and fast reactin [15][16]. This should not be ignored by the control strategy model.

The following control strategy development objectives were identified as necessary for tight Kappa control:

- Accurate dead time compensation

- Accurate model predictions over time and varying operation conditions

- Self-checking/Self-tuning

- Ease of use and support by staff unfamiliar with advanced control

  Implemetation in most DCSs

- Compatible with any Kappa sensor

The general criteria above dictated the following specific requirements:

Predictive model requirements:

- Nonlinear and adaptive with a sophisticated“continuous learn mode” (on-line identification)

- Embedded chemical reaction kinetics

CONTROL STRATEGY DESCRIPTION

The following sections describe the resulting SODAC™ (Simons' Oxygen Delignification Advanced Control) * strategy, its implementation, and mill results. Variations to this adaptive nonlinear strategy are applicable to continuous digesters, bleach plants and other non-pulp and paper chemical processes where plug flow reactors exhibiting long dead times and nonlinear reaction kinetics are involved. From the extensive simulations conducted to date and initial mill trials, it appears the strategy has met all objectives. In particular, tests confirm the control strategy model’s ability to correct itself even when every model parameter is in error compared to the real plant.

It is well documented that the majority of model based adaptive control installations are based upon linear control theory (and associated linear models) due to the complexities of designing/implementing truly robust **nonlinear** model based adaptive control. The strategy presented in this paper can be considered a modified form or an extension of IMC (Internal Model Control methodology) [18]. The significant development presented in this paper is the result of integrating nonlinear models with recent linear adaptive control developments and on-line identification techniques in a manner which reduces the historic complexity of nonlinear adaptive control. This technique incorporates Nonlinear Mapping Control (NMC™) since it allows mapping the nonlinear portions of a problem into the linear domain where linear state space models can be more easily integrated to provide model adaptation. The nonlinear portions of the model actually reduce the work of the adaptive control mechanisms thereby increasing its robustness under varying real world conditions.

The control strategy incorporates a nonlinear process model with dead time compensation and an on-line correction module to assure that predictions made by the control algorithm at every sampling step are optimal. The resulting strategy has 3 manipulation variables (NaOH dosage, oxygen dosage, and inlet temperature) and 5 major feedback signals(inlet Kappa number, outlet Kappa number, oxygen dosage, NaOH dosage, and inlet temperature). **The self-checking/ self-adapting feature of the model means that its sophistication does not impact ease of use by mill personnel.**

The control strategy has five modules (See Figure 4.). Reference the appendix for more information regarding algorithm development for each module.

1. Nonlinear Model Module

The Nonlinear Model Module incorporates a kinetic model that describes the chemical reactions in the reactor. It calculates a coarse prediction of the outlet Kappa at the end of the retention time. (Other commercially available packages use a somewhat similar prediction for control without further on-line fine tuning.)

2. On-Line Correction Module (State Space Model)

The outlet Kappa number signal in Figure 3. shows that the discrepancy between the outlet Kappa number predicted by the kinetic model (Ke) and the actual outlet Kappa number(Kout), f(z), can be corrected by an adaptive state space model (see appendix) using NMC™. The model is continuously identified on-line to establish an accurate relationship between the Kappa number

Self correcting even when **every** model parameter is in error compared to the real plant

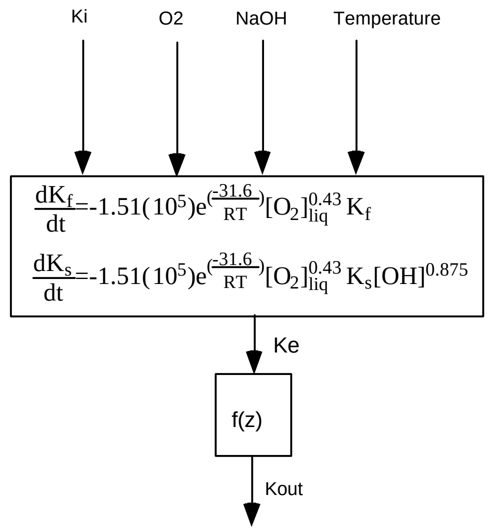

Figure 3. O_2 Delignification Reactor Outlet Kappa Number Signal Structure

*

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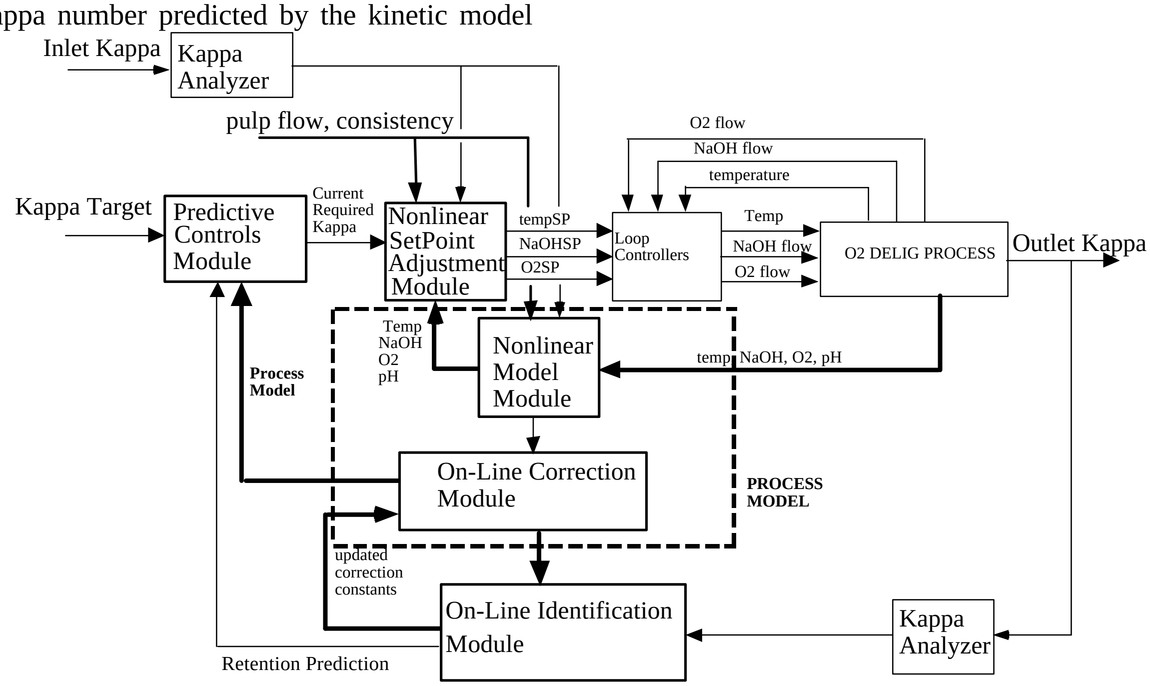


Figure 4. Adaptive/Predictive Nonlinear Advanced Control Strategy (SODAC™)

number at the end of the process. This model fine tunes the coarsely estimated Kappa number prediction. It analyzes the Kappa number and combines the results with the process knowledge "learned" by the identification module. This procedure compensate process dead time, fine tunes its previous prediction and compensates for any initially incorrect or drifting model parameters.

3. Learning Module (On-Line Identification)

The Learning Module calculates the output matrix parameters required to enhance the model prediction by correlating state variables generated in the On-Line Correction Module with the actual outlet Kappa number measurement. The output vector C(k) is updated at every sampling interval.

4. Predictive Control Module

The Predictive Control Module uses a predictive control law as the feedback control algorithm due to its simplicity of use and easy handling of varying dead-time [7].
The Predictive Control Module uses the fine tuned process model and retention prediction to calculate the current required Kappa number needed to produce the desired target Kappa at the outlet. This is accomplished by inverting the model at the end of the retention time and moving the estimate in reverse, until it reaches back to the current time step. Thus, by controlling to the currently needed Kappa number just calculated, it will provide an exact future Kappa number target at the outlet of the oxygen delignification process - if the actual process parameters do not deviate from those that have been identified up to the current time step. In practice, this will provide a very well controlled outlet Kappa number because the disturbance is "learned" and the prediction corrected by the On-Line Correction Module at every sampled step (approximately every 20 minutes).

5. Nonlinear Set Point Adjustment Module

The current required Kappa number received from the Predictive Control Module is the updated reference in setting the proper inlet temperature, caustic, and oxygen set points based on the inverted relationship established in the Nonlinear Model. Weighting factors can be assigned to the set points such that priority of adjustments can be defined. For example, caustic dosage is typically used as the main control variable while temperature and oxygen dosage ratios are kept constant until reaching a caustic limit.

Operating Modes

The control strategy has three operating modes:

1. Learn Only Mode

This is the start-up mode of the control strategy. In this mode, the control strategy learns (identifies) the particular process idiosyncrasies and adjusts its model parameters to fit. The strategy is not in control, but it is learning to predict outlet Kappa accurately (within a specified tolerance of the actual measured Kappa). When the model has learned enough to predict outlet Kappa accurately, the operator is notified to turn on the normal predictive control mode. Prediction errors are continuously monitored and corrected as part of the self-check/self adjustment features. The predicted outlet Kappa number also shows operators the reasoning behind its actions when in automatic predictive control.

2. Normal Mode (Learn Mode plus Automatic Predictive Control)

This is the normal operating mode after the initial learning phase. The strategy calculates the setpoints needed for temperature and chemicals based upon the model predicted Kappa compared to the desired Kappa target. These remote set points are sent to the cascaded PID loop controllers that regulate the desired chemical dosage and steam flow. The predicted future Kappa number and the subsequent actual sampled

Kappa number are displayed with the estimated oxygen reactor retention time. This gives operators a graphical presentation of the controller's performance. Continuous operation of learn mode assures that conditions such as changing wood species, process dynamic conditions, disturbances, sensor drift, and production changes are all compensated to maintain prediction accuracy without manual intervention.

As long as the model trends show accurate predictions, the operator should have every confidence that it will continue to do so in the immediate future. If the accuracy begins to drift uncorrected outside a specified limit, an alarm will signal the operator while the system places itself into "learn only" mode until the model predictions are of acceptable accuracy. Then the supervisory control will be automatically resumed and the operator notified. These practical features help operators develop trust in advanced control.

3. Predictive Control Only (Learn Mode Disabled)

This mode uses the last identified process model to compute proper control action. The model no longer continues to learn and correct itself (adaptation is off). This mode is used only when the oxygen delignification process has to run under invalid Kappa number readings, for example during sensor maintenance or malfunction. Conceptually this can be thought of as a fixed nonlinear model or a "sophisticated feedforward" mode. Other commercially available packages use this as their normal mode.

DCS IMPLEMENTATION

Advanced control can be implemented in almost any DCS or microcomputer with a high level language capability such as Basic, "C", FORTRAN or Pascal. The current project uses a Rosemount System 3 DCS. The control strategy is programmed using Rosemount Batch Language (modified basic) in a System Resource Unit (SRU).

Operators monitor the controller's performance by the on-line inlet and outlet Kappa standard deviations, prediction and sensor measurement comparisons and trends of the oxygen delignification process. The first installation of this strategy utilizes on-line BTG Kappa analyzers.

TESTING METHODOLOGY

The DCS was staged and tested under near "in service" conditions in Simons-Eastern's Control system staging facility in Atlanta. The DCS system was connected to a simulated process using an advanced systems test simulator (ASTS) to verify correct software implementation. (See Figure 5. for more information.) The process simulator runs a high fidelity model of the oxygen delignification process.

HIGH FIDELITY PROCESS MODEL

A design fidelity dynamic simulation model of the process was developed with the Simons IDEAS™ Simulator to represent the "actual process" in our tests [20][21]. A high fidelity was required to generate rigorous simulation scenarios that test the strategy's ability to accurately control and continuously learn under a wide range of process upset conditions, i.e., low consistency, production changes, excessive black liquor carryover.

The fidelity of the process model used for testing is summarized below.

Reactor vessel model includes detailed Chemical reaction kinetics, dynamic material,energy, and momentum balances are calculatedfor each zone in real time once every second. In addition to the high fidelity process model, a simplified "faster than real time model" of the process was used to generate rapidly changing process conditions and disturbances to verify the control strategy model could "learn and adapt" to almost any process condition. The model's high fidelity and portable DCS console interface also make it ideal for training operators on the complexities of the oxygen delignification process and importance of adaptive/predictive nonlinear advanced control.

SIMULATION RESULTS

Representative samples of generic simulation tests are included in Figures 6. and 7. (Test results shown are not tied to a specific installation.) The tests show the strategy's ability to tightly control outlet Kappa under widely varying input conditions and model parameter/actual process mismatch. As shown in Figure 7., this is due to the high accuracy of the model prediction. This is illustrated by the fact that the model prediction curve and the actual simulated Kappa measurement curve almost coincide. Also note the control improvement with the advanced control strategy over a close to optimally tuned PID with ratio feedforward control.

Many simulation runs were made under conditions of varying inlet Kappa, production rate, consistency and other disturbances. Tests show an average reduction in standard deviation of Kappa at the oxygen stage outlet compared to the inlet of 70% to 85% with large inlet disturbances. These Kappa standard deviation reductions were 3 to 4 times greater than that produced by a typically tuned PID loop with ratio control.

MILL START-UP OBSERVATIONS

The previous method of control at the mill used a chemical dosage controller to regulate the chemical addition from the dosage set points entered by the operator. This control configuration is open loop and does not attempt minimization of outlet Kappa number variation due to process complexities.

The oxygen delignification process dynamics is dominated by the nonlinear behavior of the delignification rates and the time variant nature of the process conditions. The following process characteristics were observed and verified during mill trials.

Process Definition and Verification•Nonlinearity
For a certain percent increase in chemical dosage at the inlet of the oxygen delignification reactor, one does not observe a proportional drop in Kappa number at the outlet of the reactor. The percent of outlet Kappa number reduction appears to be dependent on the inlet Kappa number, inlet temperature, and inlet chemical dosages.

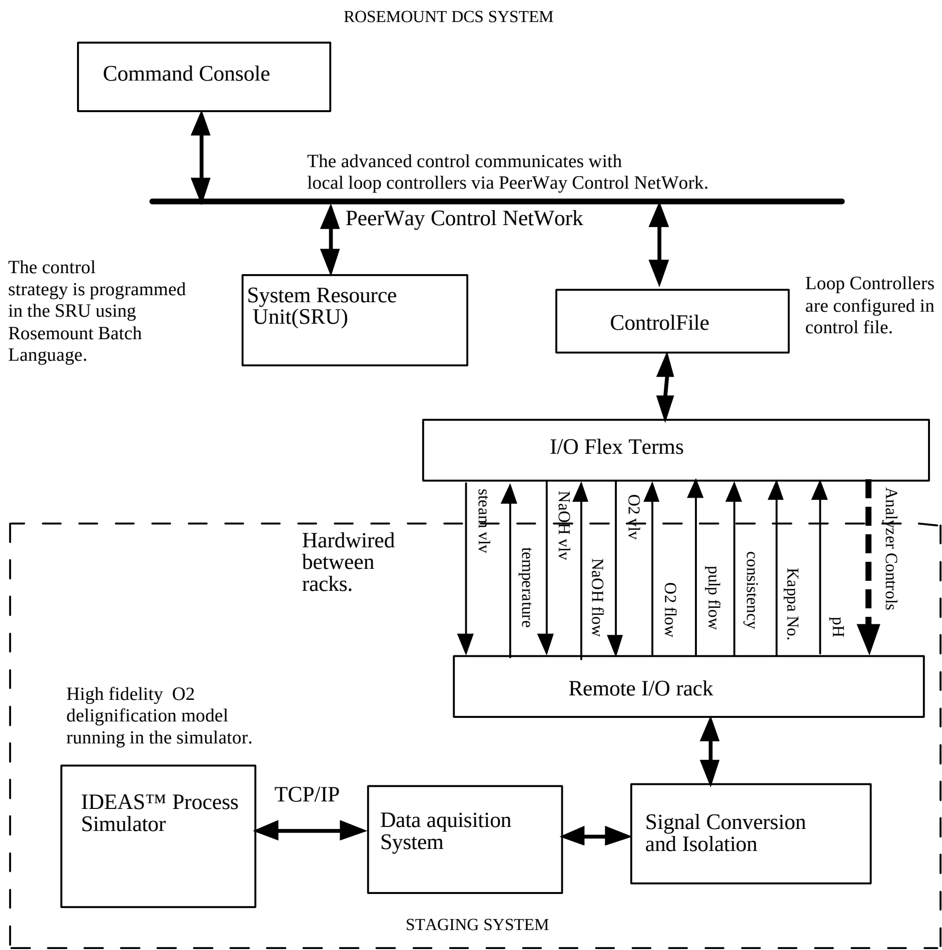


Figure 5. DCS Staging Setup

• Time Variance

For similar oxygen reactor inlet chemical dosages, inlet Kappa number and inlet temperature, we observed different percent of Kappa number reduction at the outlet of the reactor on different days. This change in the percent of reduction in Kappa number is not always repeatable. Possible explanations to this behavior are that the different defoamers added at the upstream of the process to eliminate process foaming affected the rate of O_2 delignification differently, and also, the caustic strength and oxygen purity variations are not precisely represented in the lab samples.

•Retention Time

Retention time is inversely varying with production, and is affected to some degree by reactor pulp channelling. The retention time is a pure, variable dead time in the process.

Due to the above observations, it was concluded that a fixed model based strategy would have difficulty controlling the process without periodic operator intervention and retuning of model parameters.

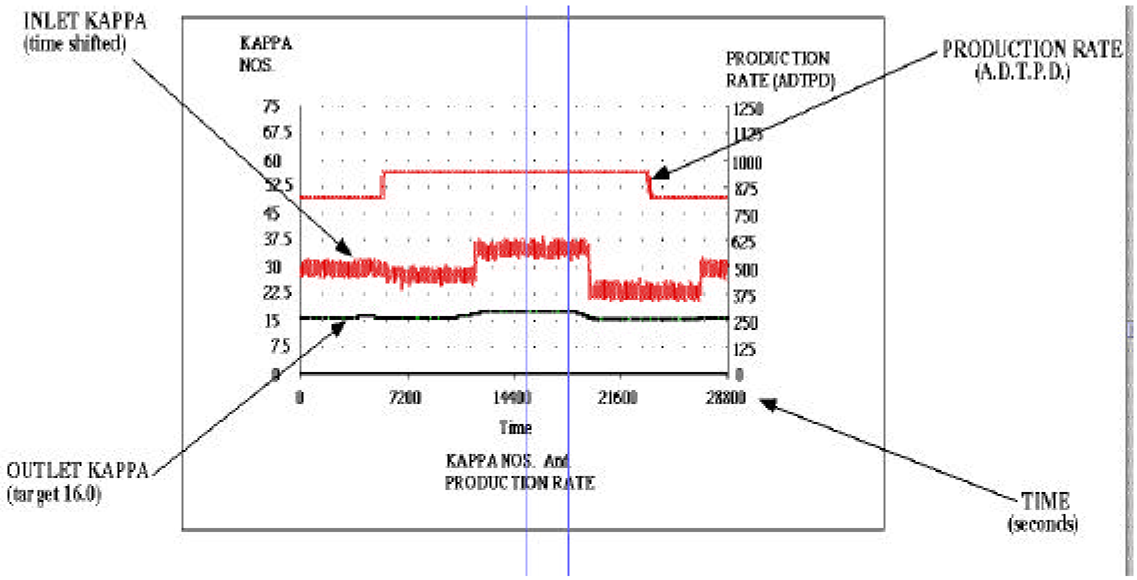


Figure 6. Oxygen Reactor Model Advanced Control Results

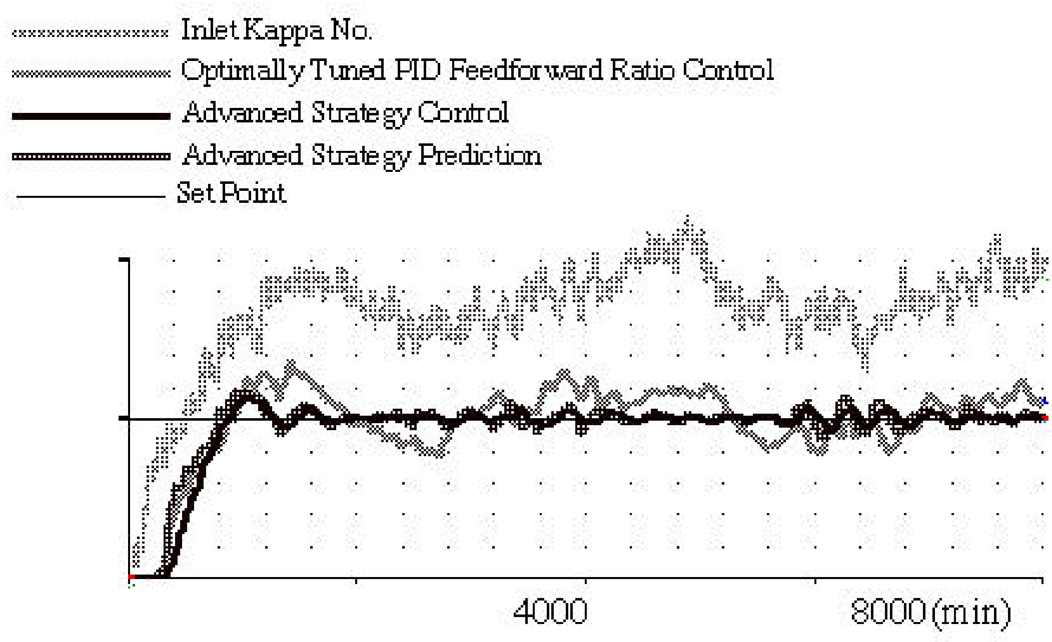


FIGURE 7. Advanced Control Strategy Simulation Comparison

MILL PERFORMANCE

Figures 9. and 10. show a 1 week period of operation before and after installation of the advanced control strategy. Figure 9. shows the reactor inlet and outlet Kappa number variations under dosage control only, just prior to mill trials of advanced control. Note the fluctuation similarities between the inlet and outlet Kappa numbers, and even the slight increase in outlet Kappa number variance compared with the inlet. This translates to an increase in outlet standard deviation relating to inlet standard deviation of almost 10%. In the adaptive nonlinear control mode, instead of using the fixed chemical dosage rate set points entered by the operator, the dosage controllers use the remote setpoints computed by the adaptive control strategy. In this mode, the operator enters the desired outlet Kappa setpoint to the control strategy directly. Figure 10. shows the resulting Kappa number variation at outlet of the reactor under the adaptive nonlinear control strategy. This shows a reduction in standard deviation of outlet Kappa compared to the inlet of 55.5%, representing an approximately 65% improvement over the period prior to activating advanced control.

Mill performance to date has shown the strategy's ability to handle the process complexities during widely varying inlet disturbances in a very robust manner. The continuous on-line system identification and adaptive control modules have remained stable during all operating conditions experienced to date as the analysis and simulations predicted. The primary requirement is to provide routine maintenance on the Kappa analyzer/sampling system to keep them in good working condition and correlating well with lab tests. General observations show that the performance increases as the severity of the inlet disturbances increases. During large inlet disturbances, the reduction of outlet Kappa standard deviation compared to the inlet standard deviation appears to be a 65% reduction. During less severe inlet disturbances standard deviation reduction appears to be between 4O% to 50%. With very low inlet Kappa standard deviations the reduction of outlet to inlet can drop to 35% to 40%.

Simulation versus Mill Performance

Most simulations were conducted with relatively large inlet disturbances, showing a 70% to 85% improvement in Kappa standard deviation compared to the apparent 65% improvement under severe disturbances in initial mill trials. There was determined to be two primary reasons for this discrepancy.

1. Analyzer Sampling Rate

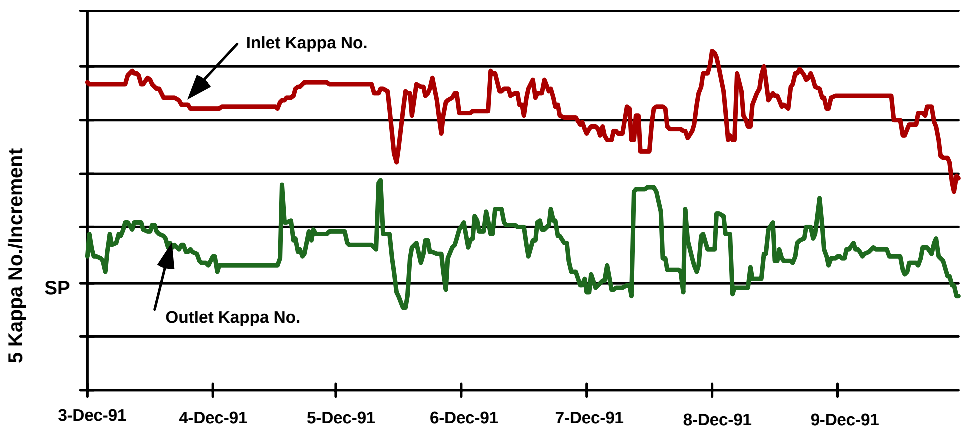
   All simulations were done assuming Kappa samples on the inlet and outlet would provide signals to the strategy at the originally planned sample rate of every 12 minutes. This sample rate would provide the strategy with a measure of inlet disturbances and a check on the accuracy of the model's prediction 5 times per hour, thereby enabling frequent adaptation and correction. The actual mill installation resulted in Kappa sample rates of 20 minutes or only 3 times per hour. These rates resulted largely from the routing required by the sample lines and location of the analyzer. It is anticipated, as the simulation showed, that performance would be better with the higher sample rate.

2. Inlet Disturbance

   The frequency of noise disturbances used in the model were much higher than the actual predominate frequencies observed at mill start-up. The reactor model assumptions which used 143 zones to approximate a continuous reactor will filter out high frequency disturbances even with no control.

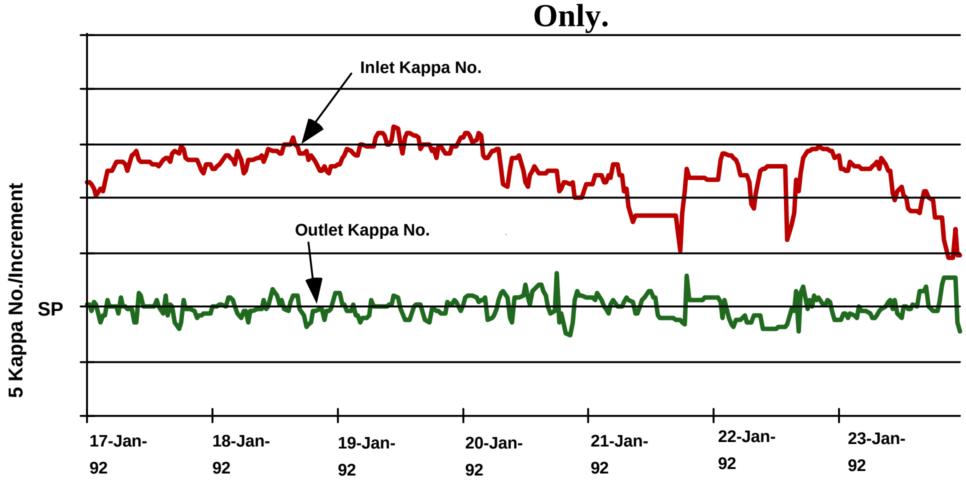
When the above two assumptions are taken into account in the simulation, the simulator predicted performance provides good agreement with that observed in the field to date.

Finally, most other model based control techniques published to date for oxygen delignification advanced control have been based primarily upon fixed model control. Consequently, it is anticipated that a robust adaptive nonlinear approach (even if no better in performance than fixed models initially) would maintain its performance over a much longer period of time without intervention by plant specialists for model tuning. This is because maintaining optimum predictive accuracy of fixed models may require periodic re-identification, re-calibration and tuning in contrast to an adaptive strategy with continuous identification "learn" modes that accomplish these tasks automatically.



StdDev In:2.02 StdDev Out:2.22 Reduction:-9.67

Figure 9. Oxygen Reactor Outlet Kappa Number Variation Under Dosage Control Only.



StdDev In:2.30 StdDev Out:1.02 Reduction:55.55%

Figure 10. Oxygen Reactor Outlet Kappa Variation Under Dosage Control and SODAC™ Regulation.

BENEFITS

Clearly, even small reductions in Kappa variation from the oxygen stage have significant effect on bleach plant operations. Reduction in standard deviation allows lower Kappa targets to the bleach plant resulting in significant cost savings in bleaching chemicals. Oxygen stage chemical usage is also optimized. Consistently, higher quality pulp is produced at lower cost and with significant reduction in environmental impact. Table 1 summarizes the benefits. Tests to date demonstrate the potential for large improvements in standard Kappa deviation under real world upset conditions simply by the addition of Kappa sensors and an adaptive/predictive nonlinear advanced control software package. Its self-checking/self-correcting features make it easy to use by operators unfamiliar with advanced control.

The availability of a high fidelity real time process model means operators can be trained to understand the oxygen delignification process in greater depth including the need for advanced control.

TABLE 1

BENEFITS OF ADVANCED CONTROL

1. Lowers chlorinated organic chemical compounds discharged to the environment including dioxins

2. Reduces bleaching chemical costs

3. Stabilizes bleach plant operation

4. Allows greater disturbances upstream of theoxygen stage and still achieve acceptable discharge Kappa numbers

5. Allows minimum Kappa number targets andensure pulp viscosity and strength are maintained

6. Easier post oxygen washing with uniform drainage characteristics

7. Reduces adverse effects of consistency variations, production changes, species changes, excessive black liquor carryover and other process disturbances

8. Allows more uniform brightness

CONCLUSION

A new technique is available for oxygen delignification advanced control that is both adaptive and nonlinear plus dead time compensating. It addresses these difficult control issues by generating reliable predictions of Kappa after “learning” specific process idiosyncrasies. There is no longer a need for fixed kinetic models that cannot adapt to changing process conditions, nor a requirement to accept the limitations of linear adaptive control on nonlinear processes. Based upon the above observations and then monitoring the operation of the advance strategy's adaptive modules in operation, it was concluded that a fixed model based strategy would have difficulty controlling this process without periodic operator intervention and retuning of the model parameters. The adaptive predictive nonlinear control strategy appears to address these complexities without operator intervention. Reductions in standard deviation of Kappa with advanced control compared to the previous dosage control only was shown to be approximately 65% in initial mill trials. This approach also has application to other complex nonlinear processes with significant dead time. This includes other bleach plant control loops and continuous digester Kappa control. With self-checking/self-correcting features advanced control need not complicate operations and maintenance. Compatibility with most DCS systems and Kappa sensors mean third party black boxes are not needed to improve plant operations.

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APPENDIX: ADVANCED CONTROL STRATEGY FORMULATION

1. Nonlinear Kinetic Model Formulation

The fundamental kinetics of oxygen bleaching have been studied over years[12][13], and several kinetic equations have been proposed by Edwards and Norberg[6], Teder and Olm[19], Hsu and Hsieh[9][10][11] and Myers and Edwards[15][16]. Among the proposed oxygen delignification kinetic equations, the rate equations presented by M. Myers and L. Edwards is used in this module due to its insensitivity to large inlet Kappa number fluctuation, and their close correlation with certain mill data.
The kinetic equations have the following form:

$$\frac{dK_f}{dt}=-1.51(10^5)e^{(\frac{-31.6}{RT})}[O_2]_{liq}^{0.43}\,K_f \qquad (1)$$

$$\frac{dK_s}{dt}=-1.51(10^5)e^{(\frac{-31.6}{RT})}[O_2]_{liq}^{0.43}\,K_s[OH]^{0.875} \qquad (2)$$

with the oxygen concentration expressed as kg/m3, and the initial fast and slow lignin conditions defined as:

$K_f=0.225K_i$

$K_s=0.675K_i$

and

K_i=inlet Kappa number.

This set of equations is solved analytically, and the resulting solution is used as the coarse prediction equation.

2. State Space Model Representation of F(z) (On-Line Correction Module)

$$\bar{X}(k+1)=\overline{A}\bar{X}(k)+\bar{B}u(k) \qquad (3)$$

$$\hat{y}(k)=\hat{C}^T\bar{X}(k) \qquad (4)$$

where

A= system matrix.
B = input matrix.
C = output matrix.
X(k)= actual state variables(correction variables).
y(k)= Kout; reactor outlet Kappa number.
u(k)= Ke; the coarse prediction.
^ = Estimated/Predicted Values

Note: The specific derivation of F(z) with NMC™ is proprietary to SODAC™ and available on a client confidential basis.

3. On-Line Identification Algorithm

The on-line identification algorithm of the Learning Module uses a modified recursive least square method [1-5][14] to identify the output vector C(k). Recursive least squares when applied to output vector (C(k)) identification can be defined as:

$$\hat{C}(k)=\hat{C}(k-1)+\frac{\bar{P}(k-1)\bar{X}(k)}{1+\bar{X}^T(k)\bar{P}(k-1)\bar{X}(k)}[y(k)-\hat{C}^T(k-1)\bar{X}(k)] \qquad (5)$$

$$\hat{P}(k)=\hat{P}(k-1)-\frac{\bar{P}(k-1)\bar{X}(k)\bar{X}^T(k)\bar{P}(k-1)}{1+\bar{X}^T(k)\bar{P}(k-1)\bar{X}(k)} \qquad (6)$$

4. Predictive Control Algorithm

The Predictive Control Module uses a predictive control law as the feedback control algorithm due to its simplicity of use and easy handling of varying dead time[7].
From equation 4, we can write the control law as follow,

$$y(k+n)=y(k)-\hat{C}^T\bar{X}(k)+\hat{C}^T\bar{X}(k+n) \qquad (7)$$

with y(k+n) equals the future set point reference at time step k+n.

Using equation 3 recusively under the assumption that future inputs u(k+1), u(k+2), ... u(k+n) equal to the current input u(k), we get

$$\overline{X}(k+n)=\overline{A}^n\overline{X}(k)+(\overline{A}^{n-1}+\overline{A}^{n-2}+..\overline{A}+\overline{I})\overline{B}u(k) \quad (8)$$

Combining equations 7, and 8 and solve for the current predictive output u(k), we obtain[17][18]

$$u(k)=\frac{y_r-(y(k)-\hat{y}(k))-\alpha\overline{X}(k)}{\beta} \quad (9)$$

with

y_r=Set Point.

$\alpha=\hat{C}^T\overline{A}^n$

$\hat{y}(k)$=estimated y(k) by the process model.

and

$\beta=\hat{C}^T(\overline{A}^{n-1}+...+\overline{I})\overline{B}$