Classical and Dynamic Matrix Control of Kamyr DigestersA Comparative Study

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Classical and Dynamic Matrix Control of Kamyr Digesters—A Comparative Study

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In Kamyr digesters, used for the production of paper pulp from wood chips, there are strong interactions between the many process variables, long time delays, and frequent disturbances. As a result, steady-state operation is difficult to attain and process control is a challenging problem. There are, however, major economic incentives to stabilize the operation of the digester. This paper investigates and compares, via extensive simulation using MATLAB, the performances of both classical and dynamic matrix controllers on Kamyr digesters, using the actual Purdue model as well as a transfer function matrix that is generated from the Purdue model and reported earlier. In classical control, the performances of both single-input−single-output (SISO) and multiple-input−multiple-output (MIMO) controllers were tested. A dynamic matrix controller that is built from four controlled variables, five manipulated variables, and two measured disturbances was designed and simulated using a discrete step-response model. Both constrained and unconstrained cases were addressed. It has been shown that a SISO feedback controller pairing the blowline Kappa number with the lower-heater outlet temperature, while treating all other major inputs as disturbances, performs much better than a decentralized MIMO controller based on a 4 × 4 transfer function matrix. The dynamic matrix controller (constrained and unconstrained) was remarkably superior over all conventional control structures.

1. Introduction

The continuous digester is a tubular reactor in which wood chips react with an aqueous solution of sodium hydroxide and sodium sulfide, referred to as white liquor, to remove the lignin from the cellulose fibers. The product of the digesting process is cellulose fibers, or pulp, which is used to make paper products. Most continuous digesters consist of three basic zones: an impregnation zone, one or more cooking zones, and a wash zone. The white liquor penetrates and diffuses into the wood chips as they flow through the impregnation zone. The white liquor and wood chips are then heated to reaction temperature and the lignin is removed through one or more cook zones. The free liquor is in either (i) cocurrent or (ii) countercurrent flow with respect to the wood chips in the cooking zones, where the majority of the delignification reactions occur. The wash zone is the end of the digester where a countercurrent flow of free liquor washes the degradation products from the pulp. This flow also cools the pulp so as to quench the reaction and reduce the damage to the cellulose fibers from continued reaction. The Kappa number is a measure of the residual lignin in the pulp and is a direct indicator of pulp quality. The objective is to produce pulp of uniform quality by minimizing the variation in the Kappa number from a target value. A schematic of external flow positions in a sectional digester model is shown in Figure 1.

Control specifications have been defined for the operation of a Kamyr digester in a major pulp and paper producer in Australia as follows:

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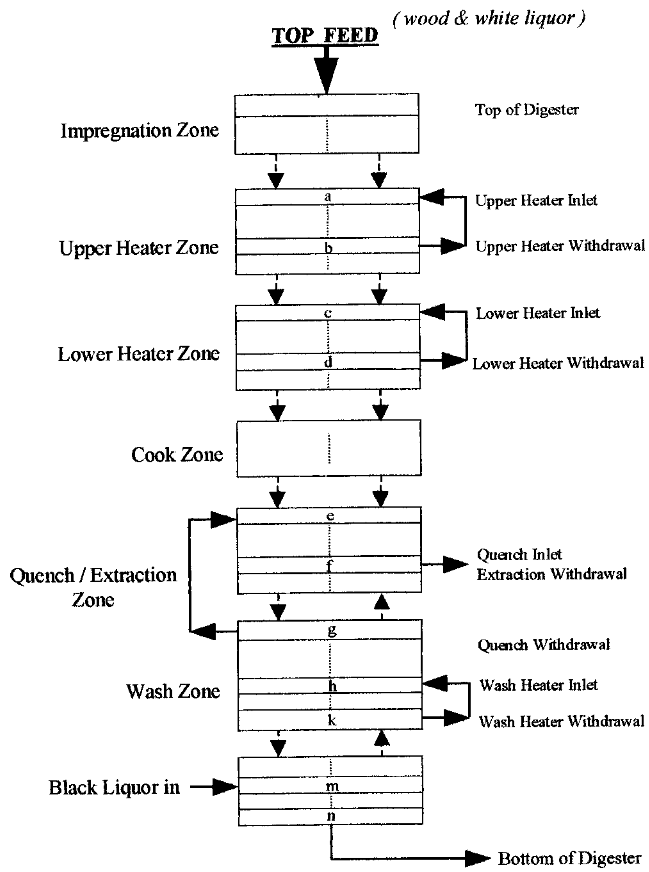

Figure 1. Schematic of external flow positions in sectional digester model.

(a) Steady-state conditions are to be re-established within 8 h of production rate on target blowline Kappa number change.

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(b) Step changes in both feed condition and chip meter speed are to be compensated for within 16 h;

(c) Aim blowline Kappa numbers may be anywhere in the range 30−50. Aim residual chemical concentrations may be in the range 5−9 g/L.

From the operational viewpoint, the two major controlled variables on a Kamyr digester are the blowline Kappa number, y_1, and residual chemical concentration, with the latter expressed as the extraction alkali concentration, y_2, and solids fraction in the extraction stream, y_5. Other controlled variables are end-of-cook temperature, y_3, and extraction temperature, y_4. The two major load variables are feed condition, or quality, m_c, which has a direct effect on the blowline Kappa number, and chip meter speed, m_s, which affects both the blowline Kappa number and residual chemical concentration. The five major manipulated variables are the white-liquor caustic concentration, m_1, and flow rate, m_2, upper-heater outlet temperature, m_3, lower-heater outlet temperature, m_4, and extraction flow rate, m_5.

Although extensive research has been carried out on the design and application of various advanced control methods to the papermaking side of paper mills, very little work has been reported on the control of the pulping side, or the continuous digester. This may be attributed to the complexity of the pulping unit and lack of sufficient understanding of the dynamics of such a process.

Cegrell and Hedqvest[1] used a simple process model of the continuous digester to control a predicted Kappa number by manipulating the cooking temperature with the model parameters updated every time a new Kappa number test is available. Michaelsen et al.[2] developed an on-line model-predictive system to control the Kappa number of a continuous digester. A real-time dynamic model, which is a simplified version of the Purdue model[3] was used along with an optimal state and parameter estimator (extended Kalman Filter) to compensate for model inaccuracy. An extended version of the Purdue model[3] was linearized and reduced[4] using Hankel-norm approximation to obtain a low-order linear model. This model was then used for linear model-predictive control with state estimation to control the Kappa number. Winsnewski and Doyle[5] investigated the issue of selecting appropriate secondary measurements for the estimation of the Kappa number in a predictive control framework using robust measurement selection tools. Amirthalingam and Lee[6] developed an inferential control scheme for Kappa number control. First, a state-space model that correlates the Kappa number to an optimally selected set of liquor measurements is identified from input−output data using a subspace identification technique. The model is then used to construct a multirate Kalman Filter and a modelpredictive controller.

This paper investigates and compares, via extensive simulations using MATLAB, the performances of both classical and dynamic matrix controllers on Kamyr digesters. In classical control, the performances of both single-input−single-output (SISO) and multiple-input−multiple-output (MIMO) controllers were investigated using the actual Purdue model as well as a transfer function matrix[7] that is generated from the Purdue model.[3] A dynamic matrix controller that is built from four controlled variables, five manipulated variables, and two measured disturbances was designed and simulated using a discrete step-response model. The step-response model is more attractive for existing plants as it only requires a series of step tests rather than vigorous modeling and model validation. From the operational viewpoint, step tests are appropriate, as the model fidelity at high frequencies is unimportant. Both constrained and unconstrained cases are addressed. A thorough analysis of the performance of both classical and model-predictive control (MPC) controllers is also presented.

2. Classical Multiloop Control System

Two configurations of classical proportional integral derivative (PID) control systems were designed and simulated for the Kamyr digester. The first configuration, the single-controller structure, is the common industrial practice for controlling the blowline Kappa number by manipulating the lower-heater outlet temperature only. The second configuration, the decentralized control structure, is a multivariable control system consisting of four SISO controllers. The purpose of these simulations is to establish a benchmark for comparison with dynamic matrix controllers.

2.1. Single-Controller Structure. In this structure, white-liquor caustic concentration, m_1, and flow rate, m_2, upper-heater outlet temperature, m_3, chip meter speed, m_s, and feed condition, m_c, are treated as loads to the process. The sampling interval used for the controlled variable, the blowline Kappa number, was 0.2 h. This is the same sampling time for the blowline Kappa number in the real digester. The lower-heater outlet temperature is used here as the manipulated variable. Both the actual Purdue model and a transfer function matrix that has been extracted from the Purdue model[3] and reported[7] were used to simulate this controller structure. The transfer function matrix is shown in the Appendix.

The PID controller settings were initially selected on the basis of the Ziegler−Nichols tuning guidelines[8] and then modified by trial and error until satisfactory performance was observed for load disturbance. The resulting controller was a proportional-plus-integral (PI) one of the form

$$G_c = K_c\left(1 + \frac{1}{\tau_I s}\right) = K_c + \frac{I}{s} \tag{1}$$

where K_c is the controller gain, dimensionless, I is the integral action in repeats per unit time, $=K_c/\tau_I$, and τ_I is the integral time, in unit time per repeat.

The optimum controller settings were found to be $K_c = -0.20$ and $\tau_I = 0.70$ h. Derivative action was found to degrade the controller performance.

The closed-loop responses, using the actual Purdue model, to a 1% step disturbance in the white-liquor caustic concentration and a unit step change in the set point of the blowline Kappa number, are shown in Figures 2 and 3, respectively. The choice of a 1% step disturbance in the load variable and a unit step change in the set point of the Kappa number has commercial importance.

It can be observed that the controller performance is stable and satisfactory except for the large dead time (in the range of 1−2 h). No overshoot exceeded the allowable transient limits of the blowline Kappa number. Settling times were typical of such a system without dead-time compensation. Similar performances were also obtained for other load variables and servo cases.

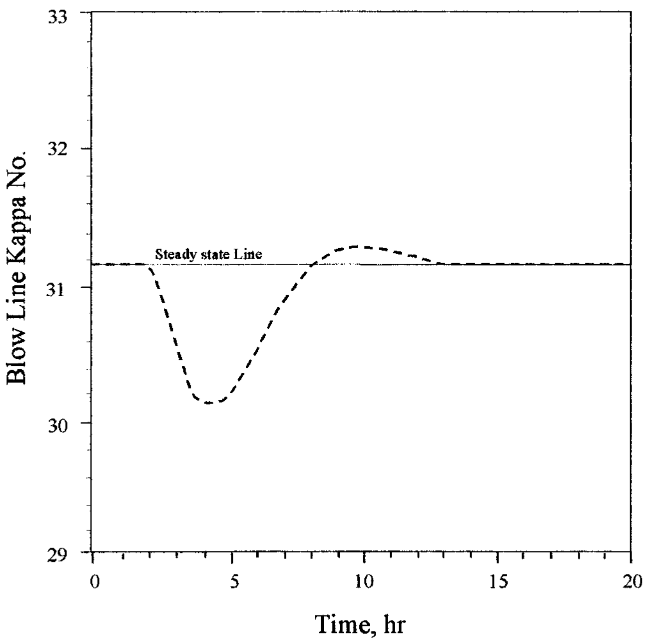

Figure 2. Response of the single-controller structure to a unit set-point change in blowline Kappa number.

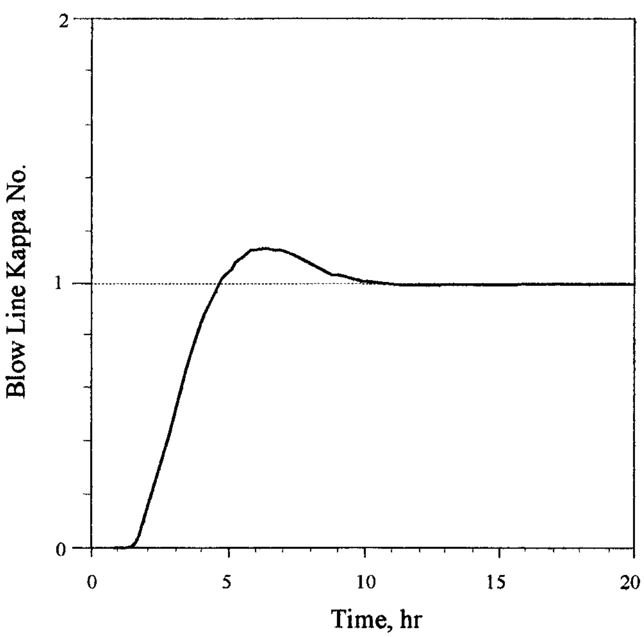

Figure 3. Response of the single-controller structure to a unit set-point change in blowline Kappa number, plus a 1% step increase in upper-heater temperature.

The performance of such a controller is expected, however, to deteriorate with frequent unmeasured disturbances and changes in the type of wood. The satisfactory performance is, probably, attributed to the assumption that the model is perfect and matches the process exactly. In reality, the actual process behavior was not as smooth as the model predicted because, basically, of model uncertainty and unmeasured disturbances.

A comparison between Figures 2 and 3, and the corresponding figures obtained using the linearized model, has shown good resemblance, indicating a good level of confidence in the approximated transfer functions.

2.2. Decentralized Controller Structure. Al-Awami and Sidrak[7] investigated process sensitivity and

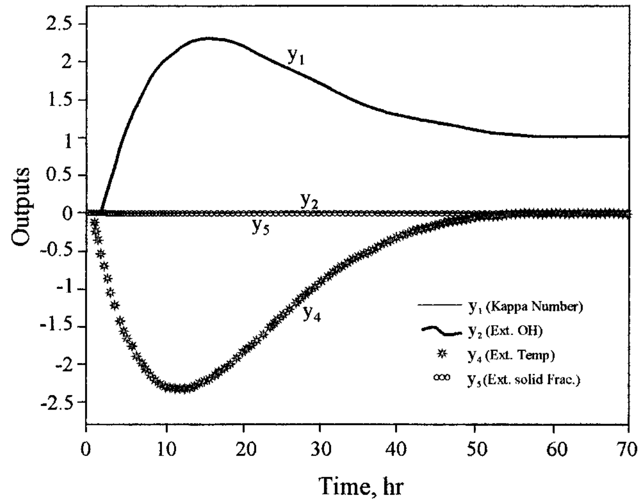

Figure 4. Response of the decentralized controller to a unit set-point change in blowline Kappa number.

interaction analysis on Kamyr digesters. Interaction analysis has been carried out using relative gain array,[9] singular-value decomposition,[10] and a condition number scaling technique to improve the ill-conditioned system.[11] Using a 4 × 4 gain matrix, the controller structure y_1-m_4, y_2-m_2, y_4-m_3, and y_5-m_1 was found to be the best for the purpose of pairing in multivariable control.[7]

The technique used for tuning the controller structure was to tune one controller at a time while the others were set to manual. Then the controllers of the extraction alkali concentration and extraction solids fraction were fine-tuned while the other two were set to automatic. This tuning technique is simple, practical, and plant-oriented.[12]

Figure 4 shows the closed-loop response to a unit step change in the set point of the blowline Kappa number.

Simulation of the decentralized MIMO controller has revealed the extent of interaction and sluggishness of such a system. Although the extraction alkali concentration and the extraction solids fraction remained practically constant, there were significant variations in the Kappa number and the extraction temperature. Magnitudes of settling times and overshoot for these two controlled variables were unacceptably large, from the operational viewpoint. When the pairing of the variables was changed in a certain manner, the resulting system was unstable. Similar results to those shown in Figure 4 were obtained for load disturbance and combined load and set point changes. In short, a decentralized MIMO system is not recommended for such a process.

3. Dynamic Matrix Control System

The present concept of model-predictive control, MPC, was introduced simultaneously by Richalet et al.[13] and Cutler and Ramaker.[14] Several attractive features of model-predictive controllers have been reported.[15] It is, however, the ability of MPC to handle information about future constraints and future inputs such as planned set point changes or forecasts of loads and disturbances that accounts for the improved performance of such controllers.

Being an open methodology, over 10 different predictive controllers, each with different properties, have been proposed in the literature over the past 15 years or so. One that is well-known is the dynamic matrix control,[14] which is, probably, the most widely used model-based predictive controller algorithm in the process industry. Dynamic matrix control has been found to improve the process-added value by between 3% and 8%, which generally provides project payback periods of 6 months or less.[16] Dynamic matrix control is normally based on a discrete step-response or impulse-response (convolution) model. The algorithm calculates moves of manipulated variables which minimize future projections of controlled variables' errors in the least-squares sense while avoiding constraint violations.

A dynamic matrix controller was designed for a 4 × 5 MIMO representation of the Kamyr digester. The four outputs are the blowline Kappa number, y_1, extraction alkali concentration, y_2, extraction temperature, y_4, and extraction solids fraction, y_5. Chip meter speed, m_s, and feed condition, m_c, are treated as measured disturbances while random unmeasured disturbance (noise) is introduced through the simulation package MATLAB. The five input variables are white-liquor caustic concentration, m_1, white-liquor flow, m_2, upper-heater outlet temperature, m_3, lower-heater outlet temperature, m_4, and extraction flow, m_5. The latter input variable, m_5, was added to give the controller an additional degree of freedom in the optimization problem.

Unlike the reported model-predictive controller on the Kaymr digester,[2,4] which used state-space models, the dynamic matrix controller presented in this work was designed using a step-response model. The step-response model is more attractive for existing plants as it only requires a series of step tests rather than vigorous modeling and model validation. From the operational viewpoint, step tests are appropriate, as the model fidelity at high frequencies is unimportant. An open-loop stable process is assumed throughout. Assume that, starting at time $(k - 1)$, all input process variables remain constant and the dynamics of the output process variables are observed. The aim is to initialize the system so that model identification starts from a steady-state point. Since the process is stable, the output will settle at a constant value after n time intervals (n is the model horizon and is chosen such that the response is, at least, 99% complete).

3.1. Simulation Results. Applying unit steps in the five manipulated variables (inputs), one at a time when the system was at rest, generated a dynamic matrix controller step-response model. These five inputs are white-liquor concentration, m_1, white-liquor flow rate, m_2, upper-heater outlet temperature, m_3, lower-heater outlet temperature, m_4, and extraction flow rate, m_5. The step coefficients were then taken at a sampling rate of 5 samples/hour up to time equals 8 h ($n = 40$) when the responses were about 99.6% of their final steady-state values with a truncation error of about 0.41%. The coefficient matrix, S, was then formed with a size equal to $(40 \times 4) \times 5 = 160 \times 5$. The computation of the coefficients is performed using least-squares-based identification, which is commonly implemented in commercial MPC.

Commercial MPC algorithms demonstrated robustness to modeling errors in various industrial applications.[17,18] However, from a theoretical point of view, especially in the case of constrained MPC, much remains to be done on the development of robust MPC controllers. It has recently been shown[17,18] that robust global asymptotic stability can be guaranteed for a set of linear, time-invariant stable systems for MPC controllers.

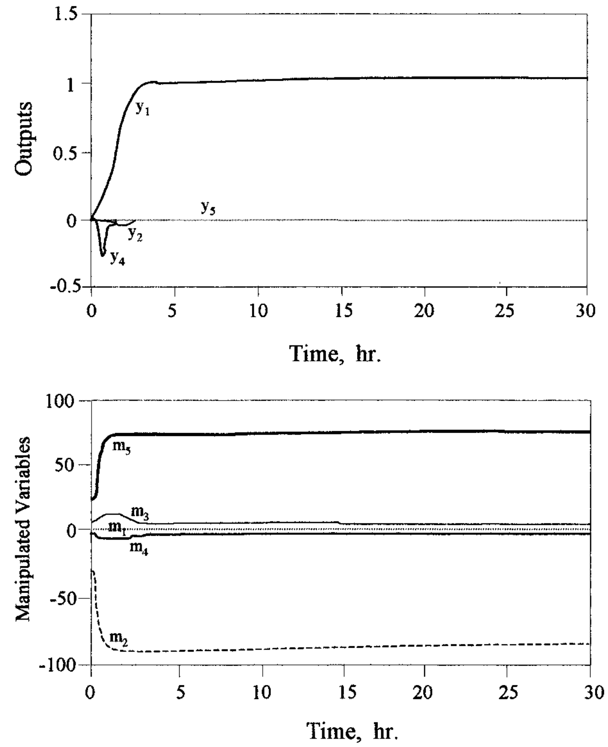

Figure 5. Response of the unconstrained dynamic matrix controller to a unit set-point change in blowline Kappa number.

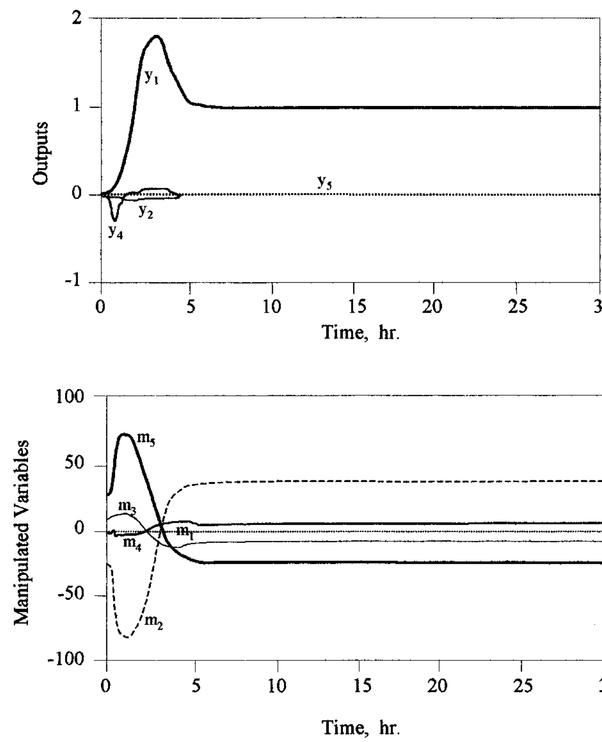

Figure 6. Response of the unconstrained dynamic matrix controller to a unit set-point change in blowline Kappa number, plus a 1% step increase in chip meter speed.

3.1.1. The Unconstrained Dynamic Matrix Control. Since unit weights on outputs and zero weights on inputs are assumed in this case, the only tuning parameters are the prediction horizon, N_p, and the control horizon, N_c. Bearing in mind that the larger the

Table 1. Comparison between Unconstrained MPC and SISO Controllers (Values Shown Are for y_1 Only)

	IAE		ITAE		t_s (h)		overshoot	
	MPC	SISO	MPC	SISO	MPC	SISO	MPC	SISO
the servo case	8.0	19.9	6.6	46.5	2.6	12	0.05	0
servo case plus a 1% step increase in chip meter speed	16.7	27.2	38.6	105.2	6	15	0.8	0.8
servo case plus a 1% step increase in feed condition	16.8	45.1	39.2	196.3	6	15	0.9	1.7
1% step increase in chip meter speed case	10.9	26.8	36.0	132.9	8	15.1	0.85	1.16
1% step increase in feed condition case	11.0	49.4	36.6	232.2	7.5	15	0.9	2.1

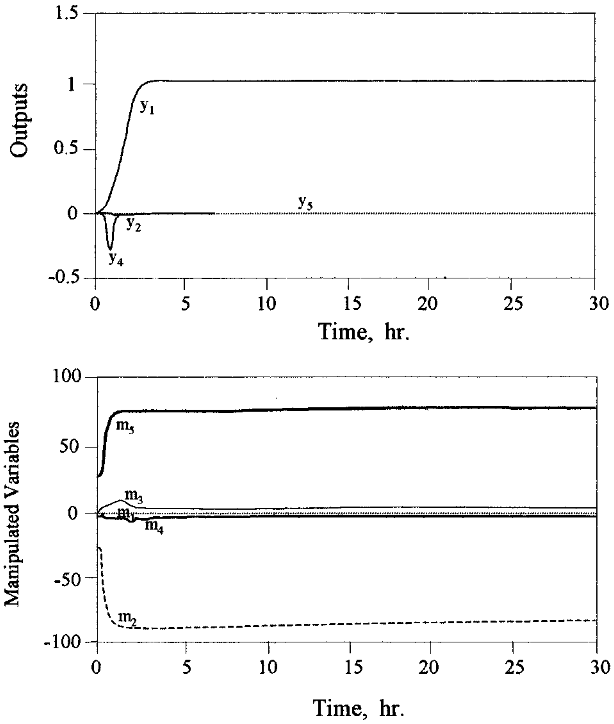

Figure 7. Response of the constrained dynamic matrix controller to a unit set-point change in a blowline Kappa number.

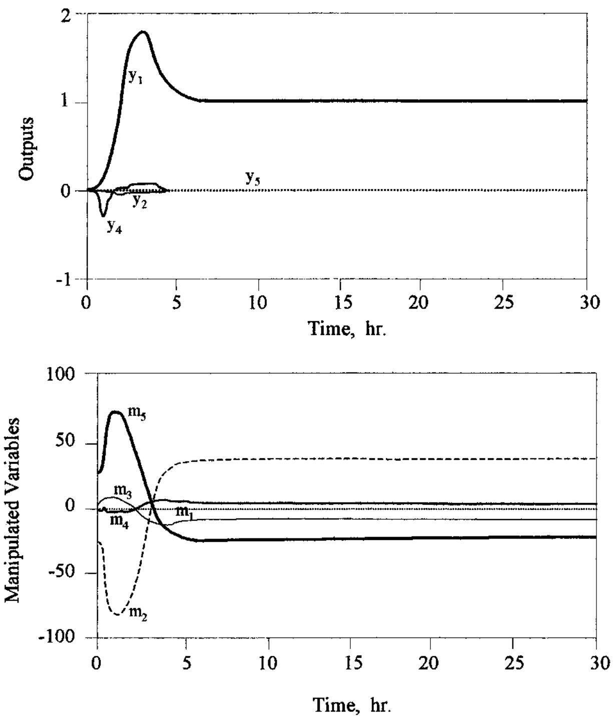

Figure 8. Response of the constrained dynamic matrix controller to a unit set-point change in blowline Kappa number plus a 1% step increase in chip meter speed.

value of N_p, the better and more stable the dynamic matrix controller performance is at the expense of computation time (Morari et al., unpublished work), a satisfactory medium was obtained with $N_p = 40$ and $N_c = 15$. The frequency was kept at 1 cycle/0.2 h.

Figures 5 and 6 show the unconstrained controller response to a unit set point change in blowline Kappa number, y_1, and to the servo case plus a 1% step increase in chip meter speed, respectively.

These curves clearly show significant improvements in the dynamic matrix controller performance over the SISO controller. Settling times have improved appreciably, a very attractive feature for a process characterized by long time delays. The IAE and ITAE errors for the common cases between the dynamic matrix and SISO controllers are shown in Table 1. Although the comparison is unfair because the dynamic matrix controller has more degrees of freedom than the SISO controller, it does give a good insight into the performance differences between the two systems. Furthermore, the comparison is based on the fact that, in a real plant, either SISO controllers (with limited degrees of freedom) or dynamic matrix controllers (with higher degrees of freedom) can be installed and used.

The controller was stable for all simulation runs. It was observed that the controller always relied primarily on manipulating the white-liquor flow rate, m_2, and extraction flow rate, m_5, to regulate the controlled variables. Practically, this is a preferred choice because it is easier, faster, and more accurate to adjust flow rates than temperatures or concentrations. For this reason, and because the variation and sensitivity of the outputs, other than the blowline Kappa number, were not significant, unit weights on outputs and zero weights on inputs were used.

3.1.2. The Constrained Dynamic Matrix Controller. Although the performance of the unconstrained controller was satisfactory, as far as the practical allowable movements in the manipulated variables are concerned, some large disturbances required excessive movements in the manipulated variables. For example, a unit step increase in the chip meter speed, which represents a 5.6% increase for the commercial base case considered in this work, necessitated a net change in white-liquor flow, m_2, of 653 (25% of steady-state value) and a net change in extraction flow, m_5, of −581 (8.6% of the steady-state value). The largest single move in m_2 was 70 (2.7% of the steady-state value). Although these changes were associated with relatively large inputs, some sort of constraint on changing certain variables is inevitable in real plant operations.

For this reason, a constrained dynamic matrix controller was considered and simulated. Constraints were introduced in the input variables only. It was decided to limit any single movement in the inputs to ±1% of their steady-state values and all manipulated variables were to be maintained within ±8% of their steady-state values. These limits are conservative and have commercial importance.

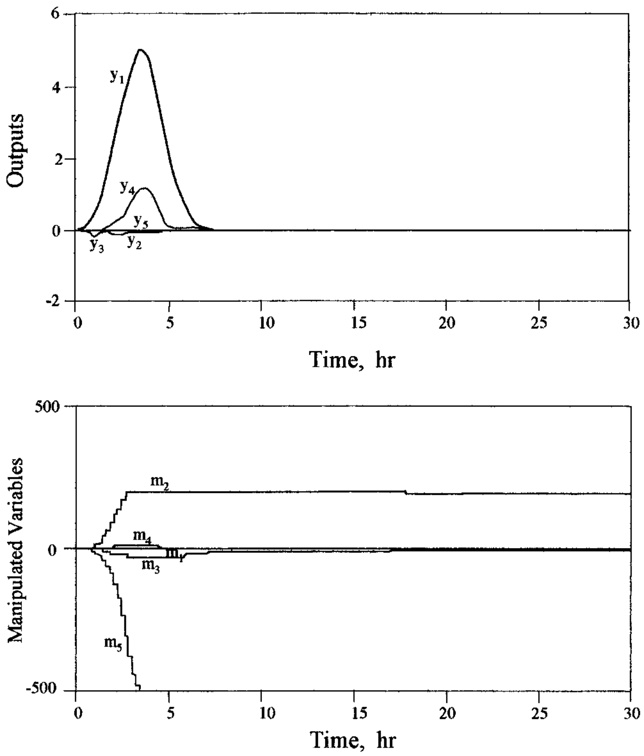

Figure 9. Response of the constrained dynamic matrix controller to a unit set-point change in chip meter speed.

Figures 7 and 8 show the constrained controller response to a unit set point change in the blowline Kappa number, y_1, and to the servo case plus a 1% step increase in chip meter speed, respectively. As can be seen, Figures 7 and 8 are similar to Figures 5 and 6, as there was no violation of constraints in the two cases considered here.

Figure 9, however, represents the constrained controller response to a unit set point change in chip meter speed. As can be seen, the total movements in the white-liquor flow rate, m_2, and extraction flow rate, m_5, are limited to 209 and 540, representing 8% of the steady-state values of these two variables, respectively.

It was observed that the computation time for the constrained MPC simulations was about 4 times larger than that for the unconstrained simulations.

4. Conclusions and Recommendations

This paper presented a comparative study, via extensive simulations, between the performance of classical and dynamic matrix controllers on Kamyr digesters, used to produce paper pulp from wood chips.

In classical control, the performances of both SISO and MIMO controllers were investigated, using the Purdue model as well as a transfer function matrix that is generated from the Purdue model. It has been revealed that a SISO controller which pairs the blowline Kappa number with lower-heater outlet temperature performs satisfactorily with somewhat long time delays in the absence of frequent disturbances. A decentralized multiloop control system, however, was shown to be severely sluggish and closed-loop unstable, with certain pairings.

In dynamic matrix control systems and, unlike the reported model-predictive control on the Kamyr digester that used a state-space model, the controller described in the present work was designed using a step-response model. The step-response model is more attractive for existing plants because it only requires a series of step tests rather than vigorous modeling and model validation. From the operational viewpoint, step tests are appropriate, as the model fidelity at high frequencies is unimportant. It has been demonstrated that a dynamic matrix controller performance is superior over the classical controller's in terms of dead-time compensation, speed of response, overshoot, and interactions. Constraints' handling was another major advantage of the dynamic matrix controller.

The implementation of the dynamic matrix controller schemes on the nonlinear Purdue model is under investigation by the authors. However, as the robustness of MPC algorithms to nonlinearity and modeling errors has been reported in the literature,[17] it is expected that similar results to those reported in this work will be obtained when the MPC algorithms are implemented on the real system.

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Appendix

The transfer function matrix for the digester is shown in Table 2.

For the load disturbances affecting the Kappa number and extraction alkali concentration, see Table 3.

Table 2.

	white-liquor caustic conc. (m_1)	white-liquor flow (m_2)	upper-heater outlet temp. (m_3)	lower-heater outlet temp. (m_4)	extraction flow (m_5)
blowline Kappa number, y_1	$\frac{-14.4115e^{-244s}}{(0.70s+1)}$	$\frac{-0.043e^{-2.09s}}{(0.84s+1)}$	$\frac{-0.375e^{-1.74s}}{(0.57s+1)}$	$\frac{-0.903e^{-1.68s}}{(0.49s+1)}$	$\frac{-0.0068e^{-0.625s}}{(1.37s+1)}$
extraction alkali, y_2	$\frac{0.277e^{-1.27s}}{(0.56s+1)}$	$\frac{8.23E-4e^{-1.02s}}{(0.586s+1)}$	$\frac{-3.6E-3e^{-0.58s}}{(0.26s+1)}$	$\frac{-9.2E-3e^{-0.53s}}{(0.27s+1)}$	$\frac{3.7E-5e^{-0.93s}}{(2.24s+1)}$
end-of-cook temp., y_3	$\frac{0.379}{(0.445s^2+0.69s+1)}$	$\frac{-2.085E-3}{(0.086s^2+0.25s+1)}$	$\frac{0.28}{(0.19s^2+0.55s+1)}$	$\frac{0.686}{(0.15s^2+0.517s+1)}$	N/A
extraction temp., y_4	$\frac{0.0117}{(0.11s^2+0.2065s+1)}$	$\frac{-0.003}{(0.119s^2+0.55s+1)}$	$\frac{0.40e^{-0.68s}}{(0.207s+1)}$	$\frac{1.08e^{-0.54s}}{(0.27s+1)}$	$\frac{-3.56}{(2.39s+1)}$
extraction solids fraction, y_5	$\frac{7.5E-3e^{-1.13s}}{(0.55s+1)}$	$\frac{1.12E-5e^{-1.26s}}{(0.6s+1)}$	$\frac{1.34E-4e^{-0.7s}}{(0.064s+1)}$	$\frac{3.3E-4e^{-0.54s}}{(0.176s+1)}$	$\frac{-9.0E-6e^{-0.11s}}{(1.78s+1)}$

Table 3

	chip meter speed (m_s)	feed condition (m_c)
blowline Kappa number, y_1	$\frac{7.68e^{-1.53s}}{(1.03s+1)}$	$\frac{6.60e^{-1.554s}}{(1.044s+1)}$
extraction alkali, y_2	$\frac{-0.0924e^{-0.97s}}{(0.675s+1)}$	N/A

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