Cascaded model predictive control of a rotary lime kiln

BY B. ALLISON AND J. BALL

Abstract: A well-operated kiln should produce high-quality lime in sufficient quantity to meet the needs of the causticizing operation, while minimizing operating costs and environmental emissions. From a control perspective, the kiln may be viewed as a multivariable distributed parameter process. Although control strategies based on univariate methods have been shown to work, what is needed is a truly multivariable strategy. In this report, we propose a cascaded model predictive control strategy that meets this need.

The lime kiln is an important unit operation in the chemical recovery and causticizing system of a kraft mill. Ideally, the kiln should be able to produce sufficient, high-quality lime to meet the needs of the causticizing operation while minimizing operating costs and environmental emissions. A well-designed control system can help to meet these objectives. Potential cost reductions from improved control result mainly from: (i) reduced requirement for purchased lime, (ii) reduced refractory damage, and (iii) lower fuel consumption. In a recent survey [1], between $400,000 and $2-million per year of savings were attributed to kiln control. According to [2], proper control of the kiln can also help to reduce total sulphur (TRS) emissions during transient operation. Recent trends in the cost of fuel are driving a renewed interest in kiln control.

From a control perspective, the lime kiln may be viewed as a multivariable distributed parameter process. The output variables to be controlled are the solids temperature at the product (hot) end, and the temperature and excess oxygen content of the combustion gas at the feed (cold) end. The manipulated input variables are the fuel flow rate and the induction draught (ID) fan speed or damper position. The lime mud feed rate is a measured disturbance. Thus, the kiln is a non-square system with two inputs, three outputs and one measured disturbance, Fig. 1. For any given feed characteristics or production rate, there is an optimal set of operating conditions that produces the best quality lime while minimizing energy consumption. The purpose of the kiln control system is to ensure consistent, high-quality lime production by maintaining these operating conditions despite the presence of disturbances. This is made difficult by significant interactions between variables, long time delays, nonlinearities, operational constraints and noisy measurements. However, as indicated above, the expected benefits in terms of cost reductions are significant.

Conventional kiln control strategies [3,4] employ classical univariate control methods based on single-loop proportional-integral-derivative (PID) feedback controllers, often supplemented with various combinations of feedforward control, deadtime compensation and decoupling to handle the long time delays and interactions. The disadvantage of this approach is that the feedback controllers are limited to a PID structure, decoupling is steady-state only, and constraints are not handled explicitly, with the result that performance is suboptimal. These disadvantages may be overcome by applying model predictive control (MPC). Some of the advantages of MPC are that it combines deadtime compensation, decoupling, feedforward control, constraint handling and optimization all in one software package. This means that the multi-step procedure involved in implementing a strategy based on classical control design methodology is replaced by a single-step design. Furthermore, MPC permits a two-degree-of-freedom design, which enables the user to individually tailor setpoint and disturbances responses to the needs of the application. Last, but not least, MPC enables the incorporation of constraints on inputs and outputs that can be used for a variety of tasks, from ensuring that actuator limits are not exceeded to running the plant at the economic optimum, which often lies at the intersection of certain constraints.

A number of studies have been conducted to investigate the feasibility of applying MPC to kiln control [5,6,7]. In all cases, MPC was used to control the product and cold-end temperatures by manipulating the fuel flow rate and the ID fan speed or damper position. It is not clear how the excess oxygen was controlled in [5], but in [6,7] output constraints were used. Reference [6] is particularly notable because of a scheme used to minimize fuel consumption. In their strategy, the product temperature setpoint was held constant to control lime quality. Minimization of fuel consumption was achieved by adjusting the cold-end temperature setpoint to always be ten degrees less than the current measurement. As the cold-end temperature is decreased, so is the excess oxygen. Eventually, the low oxygen limit is reached. This is the point of minimum energy consumption. One disadvantage of this MPC approach is that it requires the ability to handle output constraints (on oxygen in this case). This is usually achieved by solving a quadratic program (QP) on-line, and this comes at a large computational cost. Thus, MPC often requires dedicated hardware for implementation.

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To overcome this problem, we propose to use a cascaded control structure that exploits the inherent advantages of MPC (deadtime compensation, decoupling, input constraint handling) while avoiding the computational complexities of a QP. The result is a constrained, model-based, multivariable lime kiln control strategy that can be implemented on standard DCS hardware available in most mills. The remainder of the paper is organized as follows. The kraft recovery process and lime kiln operation are described in Process Description. In the next section, the cascaded MPC control strategy is described, and the basics of MPC are explained. Application of the strategy to an industrial lime kiln is described in the section on Implementation, with subsections describing the identification of process models, and the control results, including a detailed analysis of the benefits compared to manual and conventional control schemes. Finally, the conclusion can be found at the end of the paper.

**PROCESS DESCRIPTION**

In a kraft mill, the causticizing plant uses lime (CaO) to generate caustic (NaOH) from sodium carbonate (Na₂CO₃) in the green liquor. The Na₂CO₃ is formed from the black liquor in the recovery furnace, and the NaOH makes up part of the white liquor that is sent to the digester for pulping the wood chips. The purpose of the lime kiln is to recover CaO from the lime mud (CaCO₃), produced as a by-product of NaOH synthesis. This is done by calcining CaCO₃ to form CaO and CO₂. Ideally, the kiln should be able to produce sufficient, high-quality lime to meet the needs of the causticizing operation while minimizing energy consumption and total reduced sulphur (TRS) emissions.

As Fig. 2 shows, a lime kiln is essentially a very large direct-contact heat exchanger. Its purpose is to dry the incoming lime mud, which is typically 20-30% moisture, and heat it to a high enough temperature for calcination to take place. High-quality lime is very reactive. The reactivity depends on its CaO content, its particle size distribution and its porosity. The relationship between lime quality, lime mud characteristics and kiln operating conditions is not completely understood, although it is known that the temperature profile in the kiln plays a significant role. Lime quality is usually assessed in the lab by measuring the amount of residual CaCO₃ in the product.

Heat energy is provided to the kiln through fuel combustion at the hot end. Combustion air also enters the kiln at the hot end and distributes the resulting heat energy along the length of the kiln. This energy is subsequently transferred to the lime mud, which flows down the kiln countercurrent to the flow of combustion air. As the combustion air flows through the kiln, it picks up dust from the partly dried mud. Although the dust is recovered and recycled back into the feed, the CaCO₃ lost to dusting effectively reduces the production rate of lime in the kiln.

The kiln under study in this report was manufactured by FL Smidth and installed in 1965. The kiln has a diameter of 10 ft and is 275 ft in length, and was designed to process 300 air-dried tonnes/day (adt/d) of CaCO₃ with 15% recycle, resulting in 128 t/d of 90% CaO as product. Over the years the kiln has been upgraded with a second mud filter and a venturi scrubber, and will have new insulating refractory installed in the spring of 2001. From 1965 to 1993, kiln controls consisted of simple panel-mounted devises that were used by operators for manual control. In 1993, the kiln instrumentation was upgraded with new actuators and sensors, and this made it possible to implement a strategy similar to the one described in [4]. However, increased digester production rates and escalating natural gas prices provided the incentive to try to improve the control to gain even greater production and economy. The new MPC controls described here were commissioned in March 2000.

**CASCADED MPC STRATEGY**

The objectives for lime kiln control are as follows:

- Achieve tight control of the product temperature to maximize the production of consistent quality lime;
- Operate with the minimum possible excess oxygen to minimize combustion gas velocity and dust recycle;
- Operate at the minimum possible cold-end temperature to minimize energy consumption; and
- Respond to disturbances and maintain stability over a wide range of conditions.

A control strategy that meets these objectives is shown in Fig. 3. This is exactly equivalent to the strategy used in [4], but with the individual PID controllers and decouplers replaced by two cascaded MPCs. The inner-loop is a 2 × 2 MPC that controls the cold-end temperature and excess oxygen with the fuel flow rate and the ID fan speed. The outer-loop is a 2 × 1 MPC that manipulates the cold-end temperature and excess oxygen setpoints to control the hot-end temperature while optimizing (mid-ranging) the excess oxygen over the long term. In effect, both the cold-end temperature and excess oxygen setpoints are immediately manipulated when there is a setpoint change or disturbance in the hot-end temperature. Eventually, the oxygen setpoint is brought back to its target value (O₂ opt) when the cold-end temperature setpoint changes begin to take effect.

Note that the lime mud feed rate measurement is not used as a feedforward signal because the effect of feed rate changes is seen almost immediately in the cold-end temperature. The rotational speed of the kiln is determined by the feed rate of CaCO₃ according to a ratio of 3.6 r/adt. The kiln control strategy also contains a product quality controller that manipulates the hot-end temperature setpoint based on manual measurements of CaCO₃.
residual, but this is not discussed here as it was left unchanged during the course of this work.

**Generalized Predictive Control:** The particular MPC algorithm employed here is based on generalized predictive control (GPC) [8]. GPC is general enough to handle processes with any number of controlled outputs, manipulated inputs and measured disturbances. However, most of the main ideas in GPC can be conveyed by considering the univariate (single-input, single-output) case. In this section, univariate GPC is presented. Specific cost functions to be minimized for the inner- and outer-loops are discussed below in Control.

The quadratic cost function to be minimized for univariate GPC is:

\[
J = E \left[ \sum_{i=1}^{n_2} [w(t+i) - y(t+i)]^2 + \sum_{i=1}^{n_1} [\Delta u(t+i-1)]^2 \right]
\]  

where \( w \) is the setpoint, \( y \) is the controlled variable (output), \( u \) is the manipulated variable (input), \( \Delta = 1 - z^{-1} \) is the differencing operator \( z^{-1} y(t) = y(t-1) \) and \( E \) is the expectation operator. In effect, Equation (1) minimizes the predicted errors (setpoint minus output) over a future number of sampling instants, called the output horizon, defined by \( n_1 \) and \( n_2 \). The independent variables in the minimization are \( n_{\text{u, future}} \) input moves, called the input horizon. The weighting factors \( \alpha \) and \( \rho \) are used to adjust the relative importance of predicted errors and control moves, respectively. Only the first (current) input move is implemented, and the optimization is resolved with new information at the next sampling instant.

The output predictions in (1) are made using a process model that, in the case of univariate GPC, is represented by the following controlled auto-regressive integrated moving-average (CARIMA) model:

\[
A(z^{-1})y(t) = B(z^{-1})u(t-k) + T(z^{-1})\nu(t)/\Delta
\]

where \( \nu \) is an independently normally distributed (white) noise with variance \( \sigma^2 \), \( A \), \( B \) and \( T \) are polynomials in the backward shift operator:

\[
A(z^{-1}) = 1 + a_1 z^{-1} + \ldots + a_n z^{-n_1} \\
B(z^{-1}) = b_0 + b_1 z^{-1} + \ldots + b_{n_1} z^{-n_1} \\
T(z^{-1}) = 1 + t_1 z^{-1} + \ldots + t_{n_2} z^{-n_1}
\]

and \( k \) is the deadline.

**Constraint Handling:** When there are no constraints, Equation (1) may be minimized analytically. However, it is also possible to make the minimization subject to absolute constraints on the output:

\[
y_{\text{min}} \leq y(t+i) \leq y_{\text{max}}
\]

where \( i = n_1 \) to \( n_2 \), and absolute and rate of change constraints on the input:

\[
u_{\text{min}} \leq u(t+i-1) \leq u_{\text{max}} \\
\Delta u_{\text{min}} \leq \Delta u(t+i-1) \leq \Delta u_{\text{max}}
\]

where \( i = 1 \) to \( n_{\text{u, future}} \). Since the cost function is quadratic, quadratic programming (QP) techniques are well suited to minimizing (1) in the general case of constraints on both outputs and inputs. To avoid the computational burden of a QP, output constraints are not considered here, and input constraints are enforced by using the one-step optimal saturation correction algorithm proposed in [9]. Note that the one-step algorithm is exactly equivalent to a QP when \( n_{\text{u, future}} = 1 \).

**Tuning:** The tuning parameters in univariate GPC are \( n_{\text{1, future}} \), \( n_2 \), \( n_{\text{u, future}} \), \( \rho \), and \( \alpha \).

---

**TABLE I. Tuning parameters for inner loop GPC.**

<table>
<thead>
<tr>
<th>Output</th>
<th>( n_{\text{y}} )</th>
<th>( \alpha )</th>
<th>( \lambda_d )</th>
<th>( \lambda_w )</th>
<th>( \nu_{\text{umin}} )</th>
<th>( \nu_{\text{umax}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( T_e )</td>
<td>50</td>
<td>1</td>
<td>15</td>
<td>15</td>
<td>F</td>
<td>0</td>
</tr>
<tr>
<td>( O_2 )</td>
<td>5</td>
<td>1,000</td>
<td>10</td>
<td>10</td>
<td>S</td>
<td>0</td>
</tr>
</tbody>
</table>

**TABLE II. Tuning parameters for outer loop GPC.**

<table>
<thead>
<tr>
<th>Output</th>
<th>( n_{\text{y}} )</th>
<th>( \alpha )</th>
<th>( \lambda_d )</th>
<th>( \lambda_w )</th>
<th>( \nu_{\text{umin}} )</th>
<th>( \nu_{\text{umax}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( T_h )</td>
<td>180</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>T ( e^{\text{opt}} )</td>
<td>400</td>
</tr>
<tr>
<td>( O_2^{\text{opt}} )</td>
<td>60</td>
<td>O ( e^{\text{opt}} )</td>
<td>1.75</td>
<td>-0.1,0.1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**TABLE III. Typical peak operating conditions.**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Manual</th>
<th>PID</th>
<th>GPC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feed of CaCO(_3) (adt/d)</td>
<td>410</td>
<td>480</td>
<td>460</td>
</tr>
<tr>
<td>Recycle (% of feed)</td>
<td>37</td>
<td>19</td>
<td>14</td>
</tr>
<tr>
<td>90% CaO Produced (t/d)</td>
<td>130</td>
<td>196</td>
<td>199</td>
</tr>
<tr>
<td>Hot End Temperature (°C)</td>
<td>1,037</td>
<td>980</td>
<td>965</td>
</tr>
<tr>
<td>Cold End Temperature (°C)</td>
<td>357</td>
<td>335</td>
<td>305</td>
</tr>
<tr>
<td>Fuel Consumption (m(^3)/h)</td>
<td>1,925</td>
<td>2,000</td>
<td>1,850</td>
</tr>
<tr>
<td>Energy (GJ/t 90% CaO)</td>
<td>13.8</td>
<td>9.5</td>
<td>8.6</td>
</tr>
<tr>
<td>Relative Savings (k/y)</td>
<td>0</td>
<td>900</td>
<td>1,100</td>
</tr>
</tbody>
</table>

**FIG. 4.** Cascaded GPC control of the lime kiln under variable operating conditions. Solid line is process variable, dashed line is setpoint, dash-dotted line in third plot is \( O_2^{\text{opt}} \). The temperature \( T_e \) and oxygen \( O_2 \) are operating near or at their lower constraints, minimizing energy consumption at high throughput.
α and ρ. In addition, constraints that consist of minimum, maximum and rate-of-change limits need to be chosen for the input. Consider the situation when the process may be represented by a first-order plus deadtime model, which is very often the case in the process industries. Now consider the choice of tuning parameters $n_1 = n_2 = n_3 = 1$, $α = 1$, $ρ = 0$ and $T = A$. When a step change in setpoint or an output step disturbance occurs, this controller will calculate a single control action ($n_1 = 1$) that will drive the output back to the setpoint at a point ny sampling intervals into the future. Furthermore, the return to setpoint will occur in the minimum possible time when $n_3 = k$ (recall that $k$ is the deadtime). This is called deadbeat control, and may lack robustness or require excessive control actions. Robustness is improved and control action magnitude reduced by setting:

$$T(z^{-1}) = A(z^{-1})T_p(z^{-1})$$

where $T_p(z^{-1}) = (1 - \exp(-T/n_3))z^{-1}$. Here $T_p$ is the sampling interval and $\lambda_0$ is the closed-loop time constant for an output step disturbance. Since the choice of $T$ does not affect the setpoint response in GPC, it is necessary to filter the setpoint:

$$w^f(t) = \left[\exp(-T/X_0)\right]w(t-1) + \left[1 - \exp(-T/X_0)\right]w(t)$$

and use $w^f(t)$ in place of $w(t)$ in the controller. Here, the designer is free to choose $\lambda_0$ different from $\lambda_0$, yielding a two-degree-of-freedom design alluded to earlier on. When $\lambda_0 = \lambda_0$, this GPC is exactly equivalent to Dahlin’s controller, which is a deadtime compensator widely used in the pulp and paper industry, particularly in paper machine control systems.

Of course, GPC is more general than a Dahlin controller. For example, making $n_1 > k$ detunes the controller, and in the limit as $n_3 \rightarrow 8$, GPC becomes a means-level controller [10]. Different choices for the other tuning parameters may be necessary when the process model is more complex than first-order plus deadtime. $T$ may need to be modified when the goal is to reject input disturbances rather than disturbances at the output. Finally, GPC is extensible to multivariable systems, and can handle non-square systems.

**IMPLEMENTATION**

Before GPC could be applied to the lime kiln, it was necessary to obtain process models for the inner- and outer-loops. Process modelling is covered in the first part of this section. The DCS implementation results are covered in the second part. The code was implemented on a Foxboro CP30 with 386 processor and written in HLBL (high-level batch language). The sampling and control interval was one minute in all cases.

<table>
<thead>
<tr>
<th>Control Strategy</th>
<th>Fuel Consumption (m3/adt pulp)</th>
<th>Quicklime Addition (kg/adt pulp)</th>
<th>Caustic Addition (kg/adt pulp)</th>
<th>Net Savings (k/y)</th>
<th>90% CaO Production Increase (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PID</td>
<td>51.9</td>
<td>7.57</td>
<td>2.41</td>
<td>Base Case</td>
<td>Base Case</td>
</tr>
<tr>
<td>GPC</td>
<td>52.2</td>
<td>3.24</td>
<td>1.00</td>
<td>175</td>
<td>5.1</td>
</tr>
</tbody>
</table>

This model exhibits a response to a step in cold-end temperature setpoint that initially goes the wrong way. The explanation for this is that the fuel flow and fan speed needs to increase together for the cold-end temperature to increase and excess oxygen to remain constant. Initially, the increase in fan speed cools the hot end. Later, the increase in fuel causes the hot end to heat up. Thus, the wrong-way response is simply due to the differing dynamic effects of the fuel flow and fan speed on the hot-end temperature. The model (4) was used to implement the outer-loop controller.

**Control:** Tuning parameters for the inner-loop were chosen according to the method discussed above in Tuning, and are shown in Table I. Thus, the quadratic cost function for the inner-loop is:

$$J_{\text{inner}} = E\left[T_p^e(t) - T_p(t + 50)\right]^2 + 1000[O_2^e(t) - O_2(t + 5)]^2$$

Here we chose $n_1 = 1$ for each input and $n_1 = n_2 = n_3$ for the outputs. When $\rho = 0$, the control move penalty terms drop completely, and $\alpha$ has no effect except at saturation. The $\alpha$ values shown above put more emphasis on control of excess oxygen than cold-end temperature in the event that either the fuel flow or fan speed saturates. Tuning of the unconstrained closed-loop response was achieved by adjusting $n_1$ and $\lambda$. The absolute input constraints for the inner-loop were determined by the operating personnel, and were fixed at $v_{\text{min}} = 0$ and $v_{\text{max}} = 2,100 \text{ m}^3/\text{h}$ for the fuel flow and $v_{\text{min}} = 0$ and $v_{\text{max}} = 1,100 \text{ rpm}$ for the fan speed. In addition, rate-of-change constraints (see Table I) were used to limit the size of any single control move. This is particularly useful during upset conditions.

The tuning parameters for the outer-loop are shown in Table II, and the quadratic cost function for the outer-loop is:

$$J_{\text{outer}} = E\left[T_p^e(t) - T_p(t + 180)\right]^2 + 400\left[\Delta T_{\text{end}}(t)\right]^2 + 1.75O_2^e(t) - O_2(t)^2$$

Again we chose $n_1 = 1$ for each input and $n_1 = n_2 = n_3$ for the output. Since there is only one output, $\alpha$ defaults to one. Furthermore, since there are more inputs than outputs, one of the inputs needs to be constrained to a steady-state
value by modifying the cost function. The excess oxygen (last term in Equation 7) was chosen for reasons mentioned earlier, and is constrained to never deviate too far from the optimization setpoint \(O_2^{\text{opt}}\) during normal operation. However, the weighting factor for excess oxygen was chosen so that the controller would contain integral action in the event of cold-end temperature saturation, i.e. an offset required to maintain the hot-end temperature at setpoint when the cold-end temperature setpoint saturates. The weighting factor for cold-end temperature determines how fast the oxygen is mid-ranged. The absolute input constraints for the outer-loop were fixed at \(u_{\text{min}} = 1\) and \(u_{\text{max}} = 5\%\) for excess oxygen and \(u_{\text{max}} = 350^\circ\text{C}\) for cold-end temperature. The lower limit for cold-end temperature was changed depending on the production rate because operating experience was that a certain minimum production rate dependent temperature was required to achieve proper drying of the lime mud prior to reaching the chain section of the kiln. As in the case of the inner-loop, rate-of-change constraints (see Table II) were used to limit the size of any single control move. Recall that the manipulated variables for the outer-loop are the cold-end temperature and excess oxygen setpoints, so the above limits apply to the setpoints only, and should not be interpreted as output constraints.

Figure 4 shows 60 hours or 2.5 days of operation with the cascaded GPC strategy and the kiln undergoing a number of large production rate changes. Apart from a disturbance coinciding with the large sudden decrease in production at the 10-hour point, which was later found to be caused by a mechanical problem with the venturi scrubber throat damper, the hot-end temperature is extremely well controlled despite frequent rate changes. The hot-end temperature 2-sigma is 32°C over the entire 60-hour period and only 21°C over the second half when the production rate is not so variable. Note that the cold-end temperature is nearly always riding the lower constraint (which is determined from the production rate). This is because the excess oxygen is above the optimization target value of 1%. In order to decrease the excess oxygen, the cold-end temperature must decrease, but then the mud might not dry sufficiently and plug the chain section. If there were no lower constraint on cold-end temperature, the controller would continue to attempt to reduce cold-end temperature at setpoint when the cold-end temperature setpoint saturates. This would eventually reach the optimization target, and thus oxygen would become the constrained variable. This is an example of how a process must sometimes be run against constraints to operate economically. Of course, part of the success of the outer-loop in providing tight control of the hot-end temperature and minimizing energy consumption is due to the inner-loop, which provides tight control of the cold-end temperature and excess oxygen via coordinated manipulation of the fuel flow and fan speed.

Table III compares several different control strategies that have been implemented on this kiln since the early 1980s. In each case, the values in the table are averages taken over a 48-hour period representing typical operating conditions for the kiln at peak production and constant CaCO₃ residual. The kiln ran under manual control until 1993 when the strategy discussed in [4] (which we subsequently refer to simply as PID) was implemented. This change brought significant benefits, including a dramatic increase in lime production and decrease in operating temperatures and energy consumption. These improvements were used to reduce the need for chemical makeup and increase pulp production. However, to allow comparisons, we have expressed the benefits in terms of potential fuel cost savings at constant production. Note that in the case of PID amounted to over $900,000 per year (see Table III). The cascaded GPC strategy was commissioned in March 2000, and is estimated to have achieved a slight (3 t/d or 1.5%) increase in lime production and further decreases in operating temperatures and energy consumption resulting in an additional $200,000 per year in potential fuel cost savings. Note that the lime production increase was due to a substantial reduction in dusting from (19% of feed or 91 t/d to 14% of feed or 64 t/d), and was achieved despite reducing the mud feed rate.

Table IV contains an evaluation of the benefits of cascaded GPC over the first year of operation, where PID control was used as the benchmark. Over the period with GPC, the kiln was able to support 2.1% more digester production while eliminating the equivalent of roughly 11 days of digester production that were formerly supported with purchased quicklime and caustic. Together, these benefits were calculated lime production increase of 5.1%. Total fuel consumption was slightly the same for the period. Thus, because of improved control, the kiln was able to carrying 5.1% more of the causticizing load without increasing fuel consumption. Had kiln production not been increased, fuel consumption would have been reduced by roughly 5%. The net annual saving in chemical makeup was estimated at roughly $175,000. Other benefits of reducing makeup chemicals are that quicklime addition causes deterioration in causticizing plant operation and caustic makeup makes it more difficult to maintain white liquor % sulphidity. We did not attempt to attach a dollar value to these benefits. It should be noted that this kiln is producing at over 1.5 times its original design production rate. Although the PID controls installed in 1993 were quite successful and represented a major debottlenecking of the kiln, GPC still allowed us to improve this operation by an additional 5%. As all the changes associated with going from PID to GPC were software related, and implemented on hardware that was already available in the mill, no capital expenditures were required. Another benefit of GPC is that it has proven to be easier to apply and maintain. Because the PID control strategy was composed of a number of separate elements (feedback controllers, decouplers, anti-windup schemes, etc.), it became somewhat cumbersome to maintain. MPC has been described as a one-stop-shop for the control of multivariable systems with constraints. Feedback, feedforward, decoupling and constraint handling are all integrated into one program. All the user needs to do is specify a model and the constraints, and choose tuning parameters with the help of simulation. This circumvents many of the design decisions and maintenance associated with applying classical univariate techniques to the control of complex multivariable processes.

**Conclusions**

From the results reported in the previous section, we can make the following conclusions:

- Substantial economic benefits may be achieved by conventional (cascaded PID) control of the lime kiln, provided the strategy addresses both hot-end temperature control and energy minimization.
objectives.
• Cascaded MPC can achieve measurably better control and greater economic ben-
  efits than conventional methods.
• In most cases, cascaded MPC can be implemented on standard DCS hardware available in most mills, thereby requiring no new capital expenditures.
• The cascaded MPC control strategy is robust and has gained operator accept-
  ance.

LITERATURE