Model Predictive Control of an industrial lime kiln

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ABSTRACT *In Model Predictive Control (MPC), the controller is not a fixed control law but is an optimization problem that is updated and solved every sampling time. This technique was applied successfully to the control of an industrial lime kiln. The parameters chosen for control were the front end and back end temperatures. These temperatures were controlled by manipulating the fuel flow rate and the opening of the ID (induced draft) fan. When the control was implemented in an actual lime kiln, it responded well to process upsets and changes in setpoints. Operators were pleased with the performance.*

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Control systems
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Recovery

Lime kilns are widely used in the paper industry to convert lime mud to lime in the recovery cycle. Because of the large quantities of lime mud handled, it is desirable to employ an effective control scheme for the economical production of good quality lime.

The lime kiln control problem is an inherently multivariable problem, and it can be tackled best if it is handled as such. In addition, it is quite important that certain process variables remain within some well-defined physical limits in order to assure safe operation of the process. These premises make the lime kiln control a good candidate for Model Predictive Control (MPC). MPC is an approach to process control based on a process model.

Equipment and control objectives

Figure 1 depicts the basic physical characteristics of a typical lime kiln. The feed end is referred to as the "back" end or the "cold" end, while the discharge end is referred to as the "front" end or the "hot" end. Lime mud is introduced into the kiln at the cold end and is converted to lime as it tumbles toward the hot end, which is maintained at elevated temperatures by a burner system. The regenerated lime is conveyed to the hot lime silo for reuse in the slaker. Detailed descriptions of the construction of various types of lime kilns can be found elsewhere (*1*).

Some of the basic physical characteristics of the industrial lime kiln used are:

- Brick lining
- Gas circulation: induced draft damper
- Heated by natural gas
- Speed of revolution: 1 rev. in 56 s
- Dams: two, one midway from the feed end to the discharge end and one a few feet from the discharge end
- "Grizzleys": eight mounted on the perimeter of the kiln with radial orientation. Passive instruments in the shape of jaws, their function is to break any sizable lime balls that may have been formed before discharging them onto the conveyor belt.

In order to design and implement the MPC algorithm, one has first to select the manipulated and controlled variables. We will start by laying down the various options available and proceed by selecting the most viable alternatives.

Starting with Fig. 1, one can see that the mud flow rate is one of the important variables because it determines the lime production rate. The specification of the mud flow rate depends on the availability of stored mud and the desired lime production rate. For these reasons, the control of

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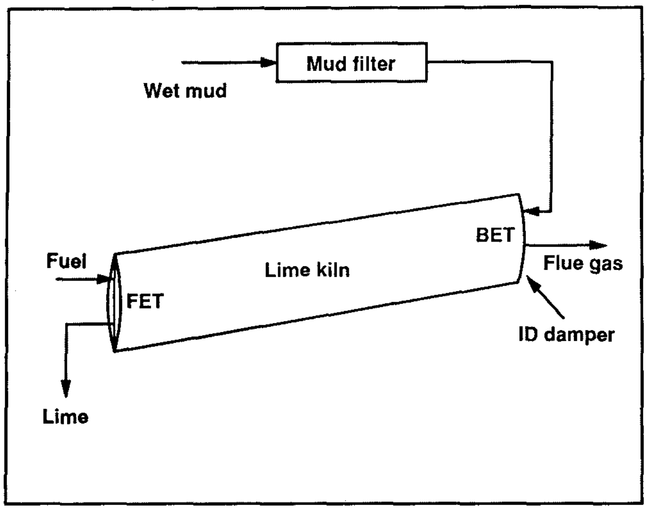
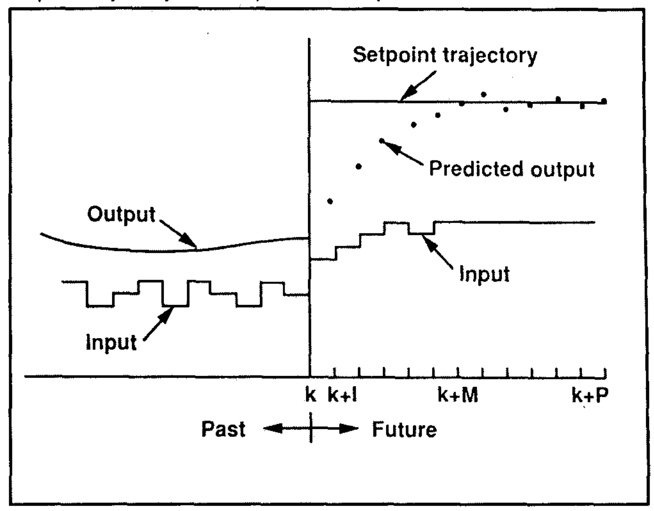
1. Arrangement of the lime kiln. (FET = front end temperature. BET = back end temperature.)



2. Moving horizon strategy minimizing the difference between the setpoint trajectory and the predicted output



the mud flow rate is separately taken care of by a dedicated PI (proportional integral) or PID (proportional integral derivative) controller. The moisture content of the mud is treated as an unmeasured disturbance.

Parameters such as the rotational speed of the kiln and the angle of inclination are not used as manipulated variables for lime kiln control because of physical considerations. To adjust the rotational speed would require extensive and expensive mechanical adjustments of the process, while the angle of inclination is usually fixed in construction.

The quality of the produced lime depends strongly upon the temperature profile along the longitudinal direction of the kiln. The temperature profile can be directly affected by controlling the front end temperature (FET) and the back end temperature (BET). The fuel flow rate and the induced-draft (ID) damper can be adjusted to control these two temperatures.

Monitoring the BET and FET is relatively a straightforward task. The BET can be monitored by a thermocouple mounted at the feed end of the kiln. Such an option provides an accurate and reliable reading of the BET. Due to the temperature elevations, the FET can best be monitored by a pyrometer, which is a reliable instrument but is subject to various types of noises introduced by the soot and flying particles inside the kiln and by the orientation of the pyrometer. Nevertheless, it is usually inexpensive and relatively straightforward to eliminate the effects of these noises by designing first-order filters.

Another control concern is the amount of oxygen in the effluent gases. This amount has to be within some upper and lower limits. If the percent oxygen in the effluent gases exceeds the upper limit, it is an indication that energy is wasted because a large amount of excess air is fed to the kiln. If the percent oxygen is lower than the low limit, it is an indication that the kiln is "overfueled"—that is, not all the fuel is completely burned—and that pollutants are being released to the atmosphere (such as carbon monoxide). The percent excess air can be easily handled by a fuel-to-air ratio controller. The amount of oxygen in the effluent gas is usually monitored by an oxygen sensor mounted at the discharge end of the kiln.

Keeping these considerations in mind, we decided that the best control results could be obtained by implementing a multivariable control system. The manipulated inputs were to be the fuel flow rate and the opening of the ID fan, while the controlled variables were to be the FET and BET.

Model predictive control

Here, we will examine the general principles of the MPC. Details may be found elsewhere (*2*, *3*).

In the linear control theory, the controller is reduced to a well-defined control law (or a mathematical equation) that is executed at every sampling time. In the MPC architecture, the controller is not a fixed control law anymore. The fixed control routine is replaced by an optimization problem that is updated and solved every sampling time. The following procedure will give a brief outline of the control structure. The development will focus on single-input-single-output; the extension to multidimensional systems, though tedious, is straightforward.

Each linear stable system can be described by a model of the form:

$$y(k+l) = \sum_{j=1}^{N} a_j \Delta u\,(k+l-j) + a_N u\,(k+l-N-1) + y_0 \qquad (1)$$

where

k = current sampling time

l = any sampling time in the future

y = process output

y_0 = initial condition of the process output

a_j = process step response coefficients

N = number of step response coefficients required to describe the dynamics of the process

u process input

$\Delta u(k)$ = control change at each sampling time = $u(k) - u(k-1)$.

The basic MPC strategy is depicted

in **Fig. 2**. At each sampling time, the controller calculates the future inputs that minimize the difference between the setpoint trajectory and the predicted output. The horizon over which we want to minimize this difference is called the "prediction horizon" (P), and the number of input changes we want to calculate is called the "input suppression parameter" (M). Obviously, the input suppression parameter is less than or equal to the prediction horizon, or $M \leq P$.

The underlying assumption in this strategy is that we have a "reasonable" model of the process. Regardless of the model accuracy, though, every real process is subject to unmeasured disturbances. Whenever a model is available for predicting the disturbance in the future, this model is used to evaluate the effect of the disturbance on the outputs. Often such a model is not available, and one resorts to a widely accepted assumption that the effect of the current disturbance will remain constant during the next prediction horizon. That is,

$$d(k+P) = d(k+P-1) = \ldots = d(k) \qquad (2)$$

These considerations indicate the necessity to modify the prediction equation, Eq. 1, to include the disturbance effects:

$$y(k+l) = \sum_{j=1}^{N} a_j \Delta u\,(k+l-j) + a_N u\,(k+l-N-1) + y_0 + d(k) \qquad (3)$$

The current disturbance is calculated from:

$$d(k) = y(k) - y_m(k) \qquad (4)$$

where

$y(k)$ = measured plant output

$y_m(k)$ = model output predicted for the present time k, calculated from Eq. 1 by setting $l = 0$:

$$y(k) = \sum_{j=1}^{N} a_j \Delta u\,(k-j) + a_N u\,(k-N-1) + y_0 \qquad (5)$$

Once the model is defined, the MPC problem is formulated by the following constrained minimization problem:

$$\underset{\Delta u}{\mathrm{Min}}\ [(y_s - y)^T \Gamma^T \Gamma (y_s - y) + \Delta u^T \Lambda^T \Lambda \Delta u\ ]$$

such that

$$y(k+l) = \sum_{j=1}^{l} a_j \Delta u\,(k+l-j) + \sum_{j=l+1}^{N} a_j \Delta u\,(k+l-j) + a_N\, u\,(k+l-N-1) + y_0 + d(k) \qquad (6)$$

and

$$y_{\min} \leq y(k+l) \leq y_{\max}$$
$$u_{\min} \leq u(k+l) \leq u_{\max}$$
$$\Delta u_{\min} \leq \Delta u(k+l) \leq \Delta u_{\max}$$

where

Δu = vector of computed future inputs $[\Delta u(k) \Delta u(k+1) \ldots \Delta u(k+M-1)\,]^T$

y_s = setpoint trajectory over the prediction horizon P $[y_s\,(k+1) y_s\,(k+2) \ldots y_s\,(k+P)\,]^T$

y = predicted output over the prediction horizon P $= [y\,(k+1) y(k+2) \ldots y(k+P)\,]^T$

Λ, Γ = weighing matrices specified by the designer.

In the objective function, the difference between the setpoint trajectory and the predicted future output is minimized along with the magnitude of the required control changes. The solution to the optimization problem produces a vector of inputs of length M. At each sampling time, only the first computed control move $\Delta u(k)$ is implemented. During the next sampling time, the disturbance is reevaluated using Eq. 4, and the optimization problem is solved again. This procedure is followed for all subsequent sampling times at which control action is required.

This formulation introduces a number of parameters that can be utilized as tuning parameters. Briefly, these parameters are:

P_i = length of the prediction horizon for each output

M_i = length of the input suppression parameter for each input

Γ = output weight or cost of deviations of the model output from the prespecified setpoint trajectory; chosen to be a diagonal matrix

Λ = input weight or cost of the size of the applied changes of inputs; chosen to be a diagonal matrix.

Actual implementation

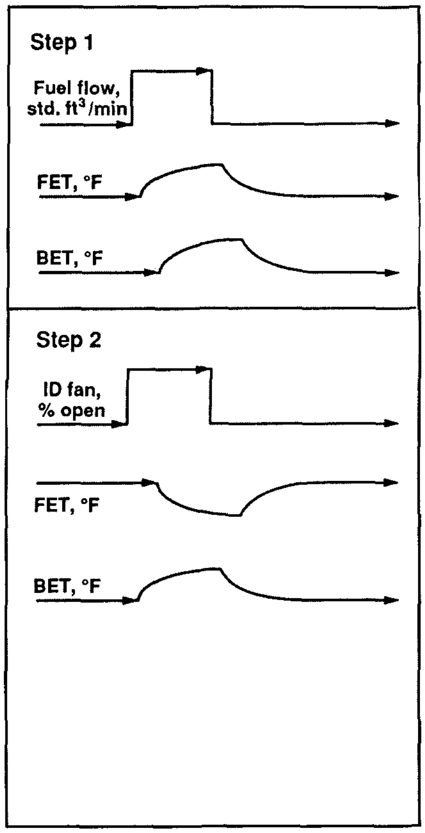
As stated, our chosen control strategy was to keep the outputs FET and BET at some desired setpoints by manipulating the fuel flow rate and the ID damper. The MPC requires dynamic models that describe relationships between the two manipulated inputs and the two controlled outputs.

Implementation strategy

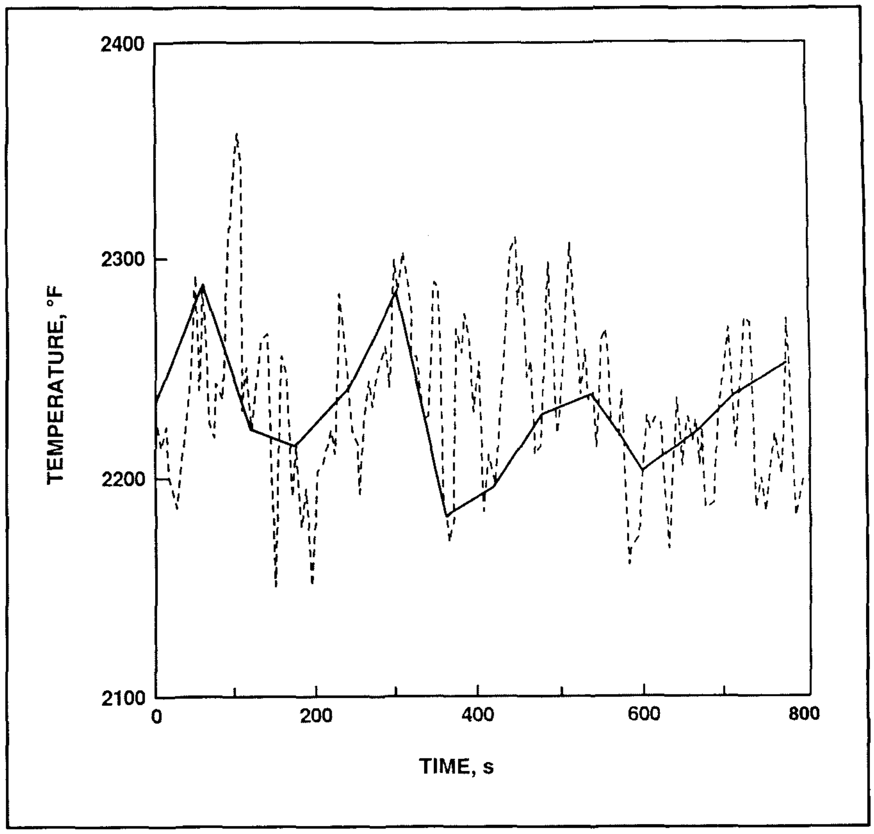
For model identification, we employed step testing on the actual kiln. The strategy was as follows: Turn the kiln on manual, let it reach a steady-state value, step up the fuel, let it reach a steady state, and then return the fuel flow to its original value. Allow the process to reach its steady state and repeat the same procedure with the ID damper. **Figure 3** shows the BET and FET expected behavior as predicted from first principles.

Real processes do not behave the way they are expected to, however, because various unmeasured disturbances may enter the process during identification and because noise may corrupt the process signal. As shown in **Fig. 4**, the noise in the FET measurement makes it very difficult if not impossible to identify any quantitative model. In some runs, the noise had a spread of 200°F, which is roughly two-thirds the size of the operating window for the temperature. Attempts to identify the source of the noise did not produce any results. We were only able to find out with a high degree of certainty that the noise had a regular periodicity of 4 min. However, none of the process variables seemed to have any such periodicity. Therefore it was decided to increase the data collection frequency. By this approach, we were able to detect the aliasing problem and isolated the more representative signal, which had about 8-9 oscillations per minute, as shown by the dashed line in Fig. 4. Further investigation revealed that the frequency of oscillations closely followed the kiln rotation. Specifically, the spikes were found to correspond to the interception of the pyrometer reading by the "grizzleys." Once the source of the noise was identified, a first-order

3. Expected identification behavior



4. Effect of aliasing. Solid line: sampling time of 1 min. Dashed line: sampling time of 5 s. By sampling every 5 s, a better representation of the noise emerged, which led to its identification. The "grizzleys" were the cause.



digital filter was designed to eliminate the noise. Filtered data are shown in **Figs. 5-8**.

Next the models were assumed to be first order with time delay, and they were fit to the data by using linear least-squares parameter fitting.

The resulting transfer function model is shown below:

$$\begin{pmatrix} y_{\mathrm{FET}} \\ y_{\mathrm{BET}} \end{pmatrix} = \begin{pmatrix} \dfrac{1.66}{39s+1} & \dfrac{-1.74e^{-2s}}{4.4s+1} \\ \dfrac{0.34e^{-s}}{8.9s+1} & \dfrac{1.40e^{-s}}{3.8s+1} \end{pmatrix} \begin{pmatrix} u_{\mathrm{fuel}} \\ u_{\mathrm{damper}} \end{pmatrix} \quad (7)$$

In addition, the operating window of the kiln is given in **Table I**. The constraints of the upper and lower limits were derived from physical and safety considerations as suggested by the kiln operators.

y_{FET}. The upper limit and lower limits are dictated by quality considerations. If the FET goes above 2250°C, the lime produced will have inferior reactivity characteristics. Temperatures below 1950°C indicate that not enough energy is supplied to the process. As a result, it is possible that not all of the carbon dioxide is removed from the calcium carbonate compound.

y_{BET}. The upper limit is dictated by process safety considerations, while the lower limit is dictated by product quality considerations. If this temperature exceeds the upper limit for long periods, parts of the kiln may get damaged. For example, the chain used to provide larger surface area for the drying of the incoming mud may burn. To guarantee that all of the undesirable CO_2 has been driven away from the lime mud, the BET has to remain above the lower limit.

u_{fuel}. The upper limit is defined by the air delivery capabilities of the air supply line. Even though the fuel line is capable of delivering larger flows, the installed equipment cannot deliver enough air to burn any additional fuel satisfactorily. Therefore, if the upper limit is exceeded, then there is a good chance that the percent oxygen in the flue gas will go out of acceptable limits. The lower limit is imposed for safety purposes: low fuel flow may result in flame loss.

u_{damp}. Openings of the damper beyond the upper limit result in rapid circulation of the gases and waste of energy. Openings below the low limit hinder the circulation too much, and such a situation may introduce increasing back-pressure with hazardous results.

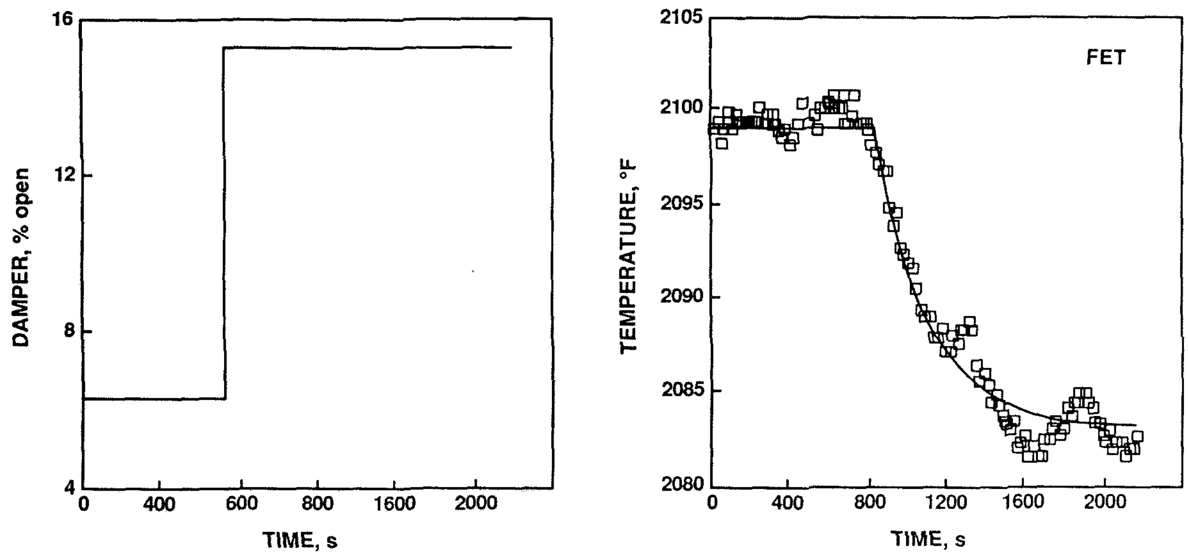
Δu_{fuel}. Changes in the fuel flow rate exceeding these limits may cause flame suffocation or flame blow-out. Loss of the flame is considered to be a hazardous situation.

Δu_{damp}. Large changes in the damper opening may cause flame loss due to flame blow-out if the damper is opened too much, or they may cause high back-pressure if the damper closes fast.

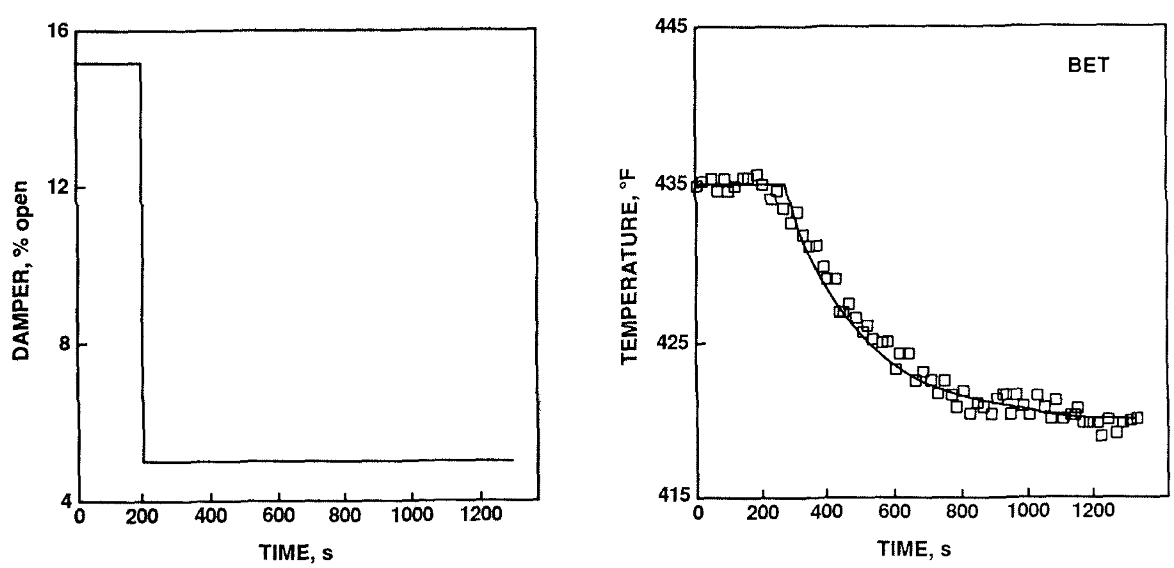
After the model was identified and the operating constraints were formulated, the MPC algorithm was easily configured into the existing data acquisition and control architecture.

To reduce the large number of tuning parameters available in the MPC algorithm, we decided to make

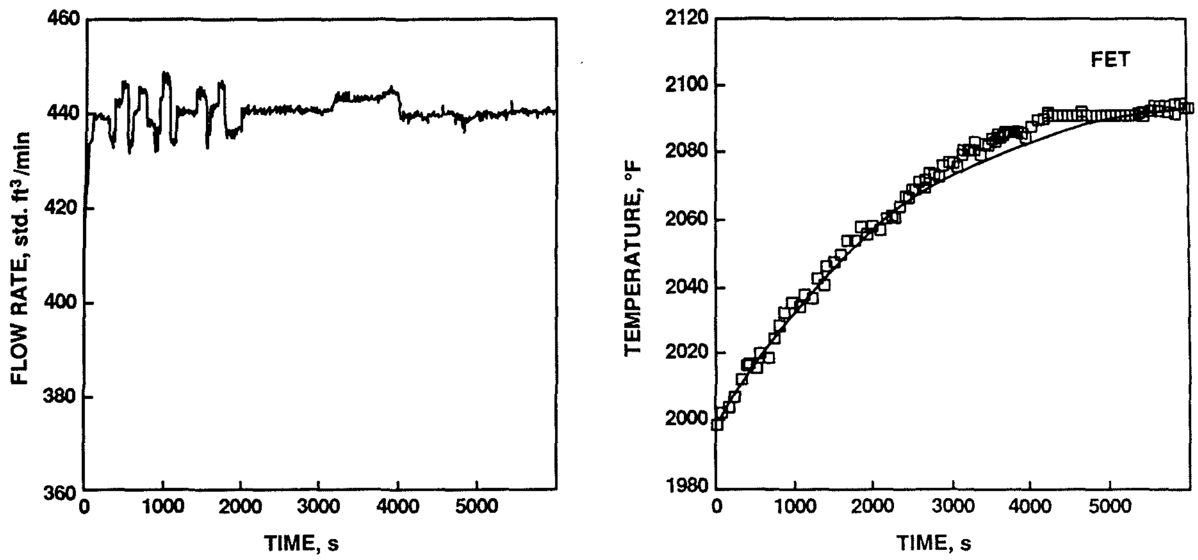
5. FET vs. damper opening. Squares: filtered process data. Solid lines: fitted model.



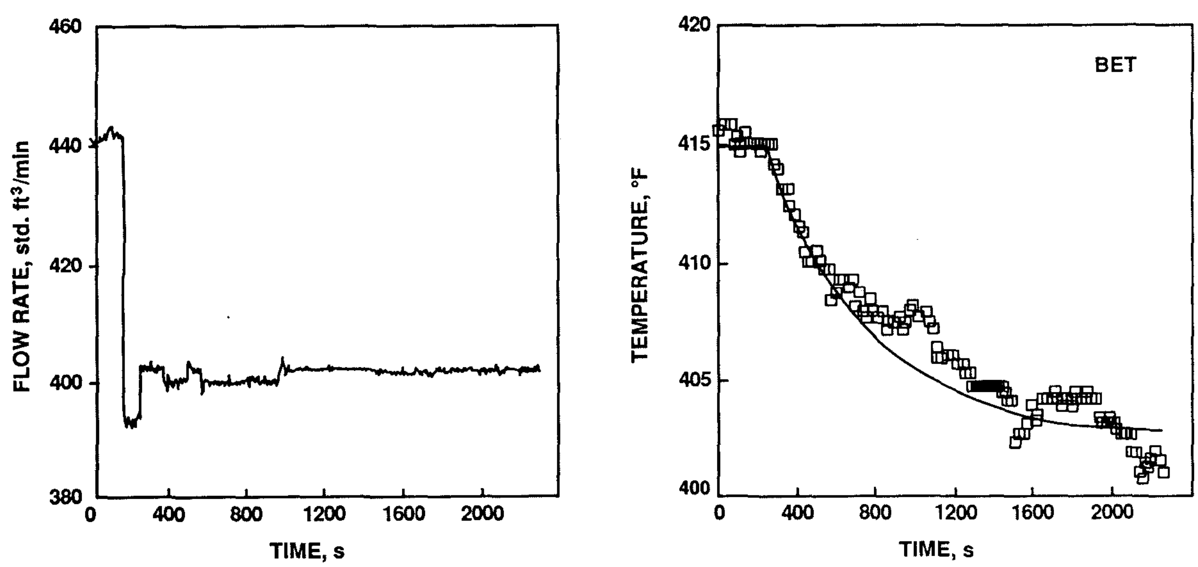
6. BET vs. damper opening. Squares: process data. Solid line: fitted model.



7. FET vs. fuel flow rate. Squares: filtered process data. Solid line: fitted model.



8. BET vs. fuel flow rate. Squares: process data. Solid line: fitted model.



I. Operating limits for the kiln

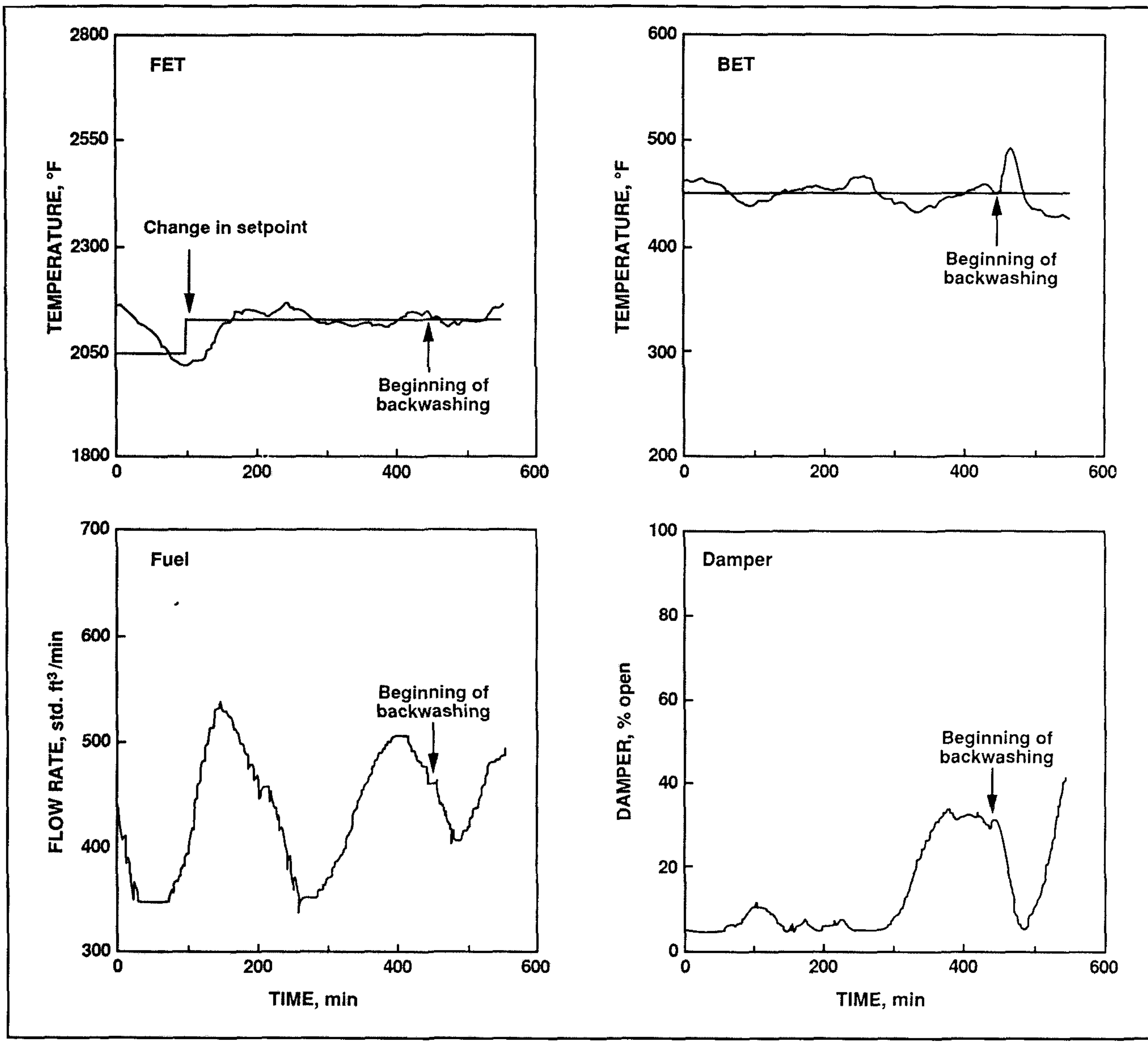
	Low	Nominal	High
y, process output			
Front-end temp., °F	1950	2090	2250
Back-end temp., °F	350	425	480
u, process input			
Fuel, std. ft³/min	350	410	600
Damper, % open	2.5	12	40
Δ*u*, control change			
Fuel, std. ft³/min	-15	...	15
Damper, % open	-5	...	5

II. MPC tuning parameters for data in Fig. 9

	y^*	Δ*u* Fuel	Δ*u* Damper
P	20	...	...
Γ	1.0	...	...
M	...	10	10
Λ	...	1.0	1.0

*For FET and for BET.

9. Setpoint tracking with MPC, showing the operator's change in FET and the initiation of backwashing.



some simplifications that would not result in substantial loss of control quality. Consequently, all controlled outputs have the same length of prediction horizon, and all input suppression parameters have the same value. Each manipulated input is subject to the same weight, for the entire duration, of the input suppression parameters for each sampling time, and each controlled output is subject to the same weight, for the entire duration, of each prediction horizon for each sampling time. In addition, all input and output constraints remain constant for each sampling time.

These simplifications gave us the flexibility to develop a relatively simple on-line tuner. Through this tuner, the operators can change the value of the input and output weights, the desired speed of response, and the input and output constraints. They could even change the process model after the controller was commissioned.

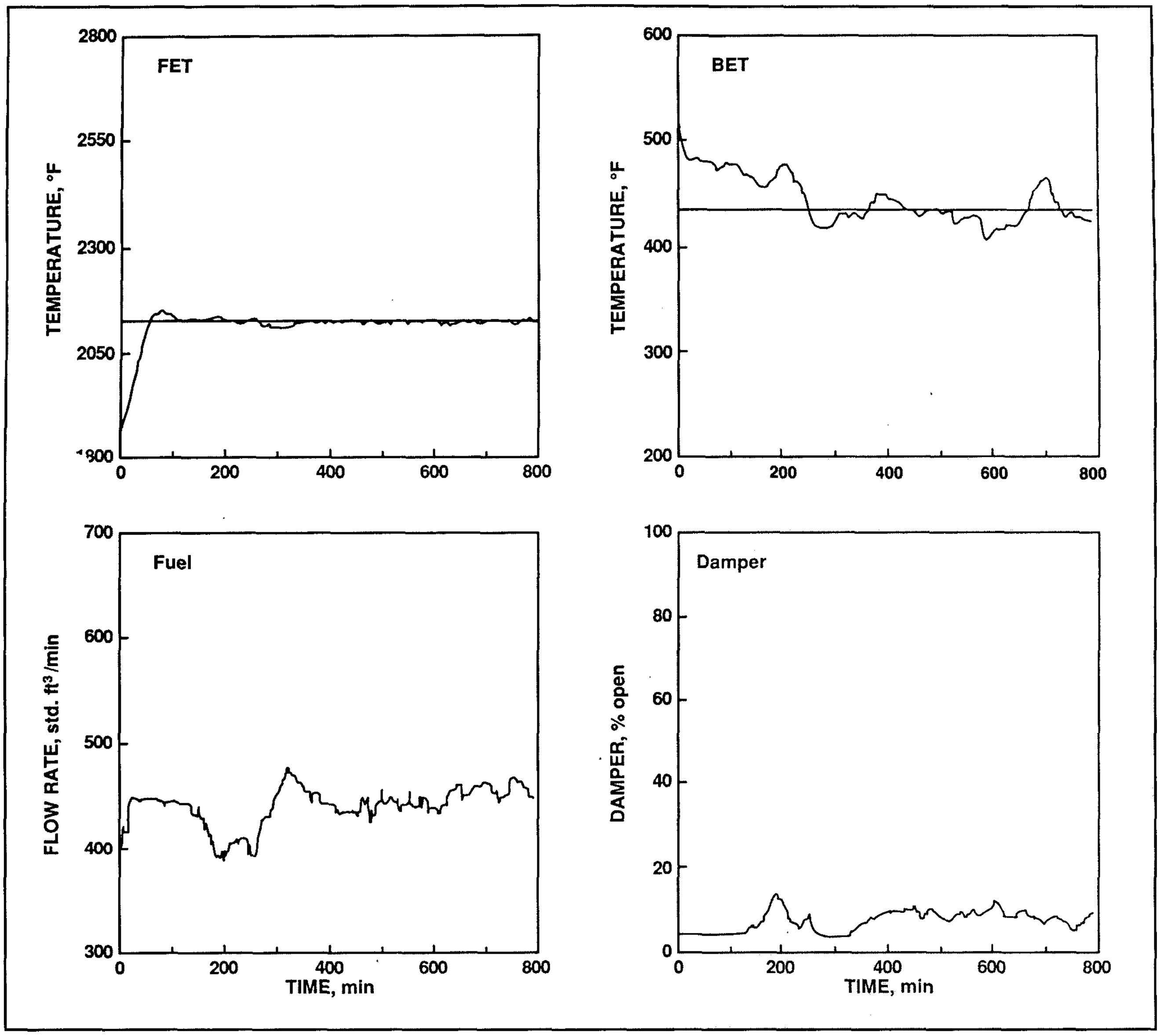
Data collected using MPC to control the kiln

No special precautions and no special treatment of the kiln were in effect while the MPC controller was controlling the process. In fact, the operators were instructed to interfere with the controller action whenever they saw fit. This situation left the MPC controller open to both unmeasured disturbances as well as disturbances induced by the operators. Interestingly enough, the operators were pleased with the controller performance, and they did not have to interfere with the controller for as long as it was in operation.

During the commissioning of MPC, attention was paid to the hard constraints only. Specifically, these were the upper and lower constraints of the manipulated inputs and the size of inputs as defined in Table I. No hard constraint violation was observed during the MPC implementation. **Table II** gives a representative set of tuning parameters used in the runs we will look at here.

Figure 9 shows the setpoint tracking capabilities of the controller. The instant MPC was turned on, the FET was far away from the setpoint. The

10. Before the controller was turned on at $t = 0$ min, the mud flow had been interrupted, and the operators had turned the burner off. Consequently, this scenario is similar to a startup procedure.



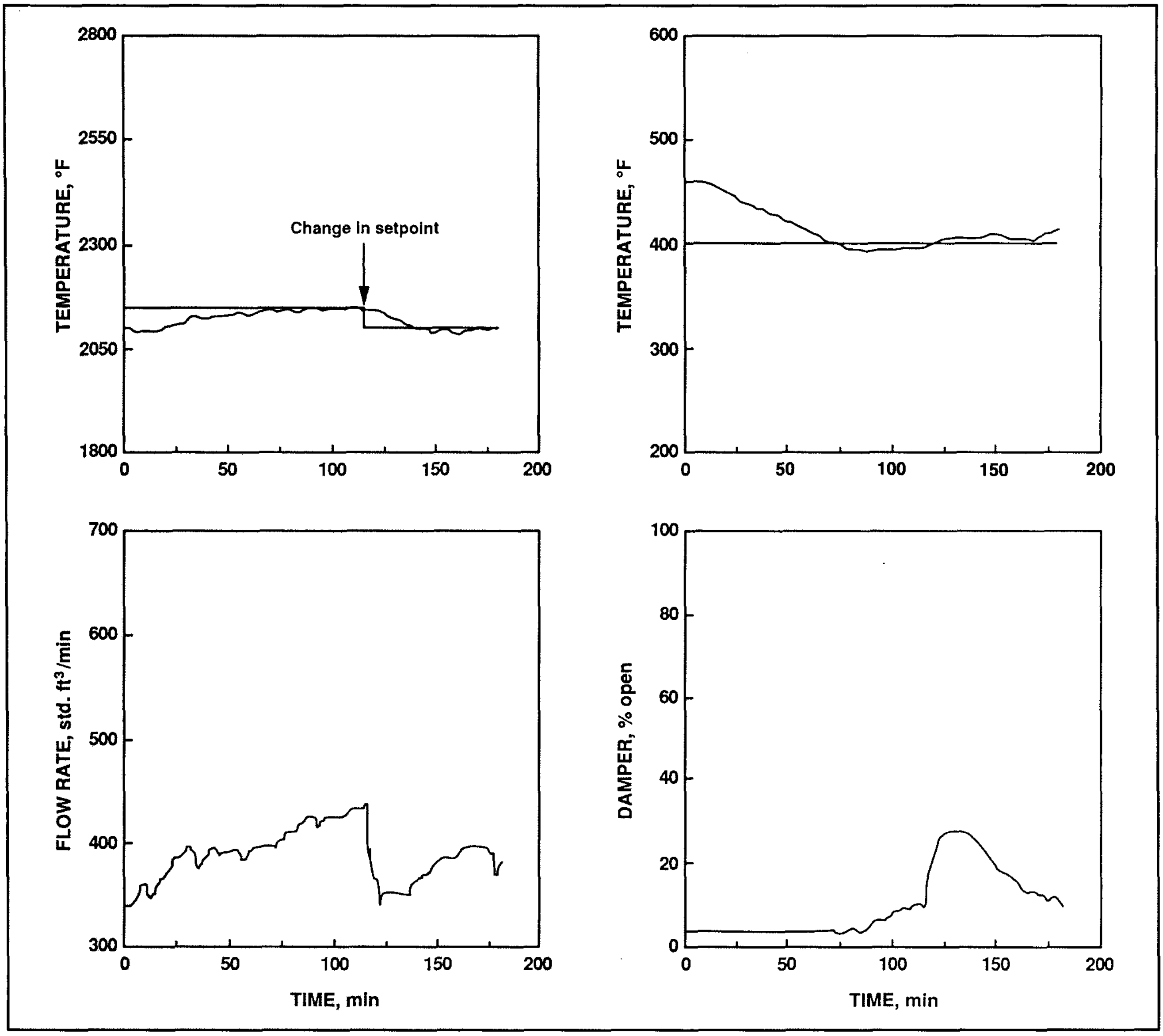
controller realized the situation and pushed both the FET and BET toward their setpoints. Before the temperatures had the chance to settle to their setpoints, the setpoint of the FET was changed by the operator. Once more, the MPC moved the outputs toward their new setpoints.

At time $t = 450$ min, a major disturbance enters the system. The mud flow is interrupted for filter backwashing. During backwashing, the operator stops the mud flow and physically washes the filter with running water. This procedure takes place with a relatively steady frequency of once or twice per operator shift. It usually lasts anywhere between 10 min and 30 min. Even after such a drastic disturbance, the controller takes the right corrective action and drives the controlled outputs toward the desired setpoints. The run was terminated before the controller had the time to return the outputs to the exact setpoints.

In addition to the satisfactory setpoint tracking performance, one can conclude by observing the recorded data that the controller has excellent disturbance rejection characteristics. This conclusion can be drawn from the vigorous "cycling" behavior of the manipulated inputs. It is clear from the fuel rate plot in Fig. 9 that during this run the process has been subject to some major disturbances with an approximate period of 200 min. Nevertheless, the controller suppresses most of the effect of this disturbance and proceeds to implement the new setpoint.

Figure 10 presents a scenario similar to a startup procedure. Before the MPC controller was turned on for this run (i.e., before time $t = 0$ min in Fig. 10), the kiln experienced a lengthy mud flow interruption. Because of the mud flow failure, the operators had to turn the burner off to avoid burning the drying chain, but as a result the FET dropped to very low levels. The MPC controller was turned on after the mud flow was restored. Even though the controller took over with the process being far away from the setpoint, it managed to

11. Constraint handling with MPC, showing the gradual increase in fuel rate, the change in damper position from almost closed to open, and the change in FET setpoint



drive both temperatures to the desired operating region in relatively short time.

Figure 11 illustrates the constraint handling capabilities of MPC. Initially the process is drifting along the process constraints. In particular, the damper is closed as much as the constraints permit. Gradually the MPC controller increases the fuel flow, allowing the damper to open and move into the feasible operating region. By doing so, it drives both outputs closer to their setpoints. At time t = 110 min, an FET setpoint change was requested. Again the controller responds in the right way by moving the FET to the new setpoint, while acting within all the constraints.

Conclusions

The implementation of MPC on the industrial lime kiln was successful. The model predictive control technology can be easily employed on problems related to the paper industry. A major advantage of the method is that it can function satisfactorily in an uncertain process environment dominated by disturbances and lack of good models. In addition, due to the number of tuning parameters available, one can easily handle process constraints and tune the MPC controller to produce dynamic behavior acceptable to the process operators.□

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°C = 5/9 (°F - 32°)