

BrainWave[®]: Model Predictive Control for the Process Industries

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1. Introduction

This chapter describes the development and application of a model-based predictive adaptive (MPC) controller, commercially known as BrainWave[®]. This controller is a patented (US Patents #5,335,164 and #6,643,554) PC-based commercial software package with hundreds of installations around the world in many different process industries. The predictive control capability enables significant performance improvements compared to manual or other automatic control strategies for processes with long time delays or multi-variable interactions. Process variability reductions of 50% or more are typically achieved using this technique.

MPC technology has been used for many years in the petroleum industry but it is not yet common practice in most industries. The high cost and implementation complexity have been barriers to the wide spread use of MPC. It is therefore important that an MPC tool be designed for ease of use to reduce the cost of installation and life cycle maintenance. Model identification and controller tuning are the primary tasks involved in the installation of an MPC controller so the controller must be designed to make these functions as easy as possible. The controller should be designed to handle self-regulating systems, open loop unstable (integrating) systems, and multivariable systems, so that the one controller can be used to solve as many applications as possible, avoiding the need for the user to learn and support too many different controller designs.

BrainWave is an MPC controller that has been developed to solve the most common types of difficult regulatory control problems. It has been deployed in a wide variety of process industries including pulp & paper, mineral processing, plastics, petrochemicals, oil and gas refining, food processing, lime and cement, and glass manufacturing. BrainWave is designed for ease of use. A novel process identification and modeling method based on the Laguerre series transfer function helps to simplify the steps required to obtain a model of the process response. Internal normalization techniques simplify the setup and tuning of the controller. BrainWave is designed to control processes that are self-regulating, integrating, or multivariable, so this one MPC tool can be used for virtually all difficult regulatory control loops in a plant.

The chapter will describe the mathematics behind the Laguerre modeling method, and show the development of the predictive control law based on the Laguerre state space model used in the BrainWave controller. The user interface from the actual software implementation will be illustrated. Several application examples from the Pulp & Paper and Mineral Processing

industries will be provided that highlight the different types of regulatory control problems where MPC provides clear advantages over conventional PID type loop controllers.

2. Adaptive model-based predictive controller development

Obtaining a process response model is a key part of the implementation of an MPC controller. In our design, the controller models the system response using a generic function series approximation technique based on Laguerre polynomials. This approach provides a simple and efficient method to mathematically model the process response with a minimum of *a priori* information. It also enables the controller to perform online adaptation of the process response models automatically. These factors reduce the implementation effort and contribute to quick installation times. The adaptive capabilities assist the control technician with developing the process response models, and the default configuration of the control parameters ensures excellent control performance once the process model is obtained. These features help to ensure the same good result will be achieved regardless of the expertise level of the person doing the application. For industrial customers that operate large plants with thousands of process controllers, this benefit alone is extremely valuable.

Using these models as the basis for a predictive control design, the MPC is able to control processes with long delay or response times (or fast response processes where the time delay is a significant part of the response dynamics) better than is possible using PID type controllers. This technique can also be used to automatically model and counteract the effects of measured disturbances by incorporating them into the control strategy as feed forward variables. The use of feed forward variables is particularly important for long time delay systems so that disturbances can be cancelled much sooner than is possible using feedback control alone.

The advanced process control algorithm presented here is an adaptive model-based predictive controller that has its origins in the work of (Zervos & Dumont, 1988). They proposed the use of a state-space model derived from Laguerre orthogonal basis functions so that adaptive control could be achieved without the need to know the process order or the time delay in advance. This approach reduces the *a priori* knowledge required to develop a high fidelity model of the process transient response, thus simplifying the modeling task.

An analogy to this method is the use of Cosine functions in the Fourier series method to approximate periodic signals as is common in frequency analyzers. In this case, weights for each Cosine function in the series are determined such that when the weighted Cosine functions are summed, a reasonable approximation of the original signal is obtained. In this case the signal is represented by its frequency spectrum, with each basis function weighting coefficient representing the contribution of each frequency present in the original signal. This method is efficient due to the similarity of the basis functions in the series to the signal being modeled, and also due to the special mathematical property of the basis functions called orthogonality that ensures the unique solution of the basis function weighting coefficients in the identified model.

In process control, the process transfer functions are transient in nature and are not periodic, so Cosine functions are not an appropriate choice as a basis for the model. However, the elegance of the Fourier series technique provides many advantages such as simple and efficient model structure and excellent parameter convergence when estimating the model from observed data sets due to the orthogonality property of the Fourier series. The motivation of this research was to find an equally simple and efficient method to model the transient responses common in process control applications.

The Laguerre functions are well suited to modeling the types of transient signals found in process control because they have similar behavior to the processes being modeled and are also an orthogonal function set. In addition, the Laguerre functions are able to efficiently model the dead time in the process response compared to other suitable function sets. This Laguerre model is used as a basis for the design of the predictive adaptive regulatory controller.

Laguerre basis functions are defined by:

$$L_i(t) = \sqrt{2p} \frac{\exp(pt)}{(i-1)!} \frac{d^{i-1}}{dt^{i-1}} (t^{i-1} \exp(-2pt)) \quad (1)$$

Where L_i is the i^{th} Laguerre function, and p is a scaling parameter referred to as the Laguerre pole.

Each Laguerre basis function is a polynomial multiplied by a decaying exponential so these basis functions make an excellent choice for modeling transient behavior because they are similar to transient signals. For use in modeling processes, these basis functions are written in the form of a dynamic system. With appropriate discretization (assuming straight lines between sampling points), the orthogonality of the basis functions is preserved in discrete time.

Summing each Laguerre basis function with an appropriate weighting factor approximates a process transfer function:

$$g(t) = \sum_{i=0}^{i=\infty} c_i L_i(t) \quad (2)$$

The Laguerre function has the following Laplace domain representation:

$$L_i(s) = \sqrt{2p} \frac{(s-p)^{i-1}}{(s+p)^i}, \quad i = 1, \dots, N \quad (3)$$

where: i is the number of Laguerre filters ($i = 1, N$);

$p > 0$ is the time-scale;

$L_i(s)$ are the Laguerre polynomials.

The reason for using the Laplace domain is the simplicity of representing the Laguerre ladder network, as shown in Fig. 1.

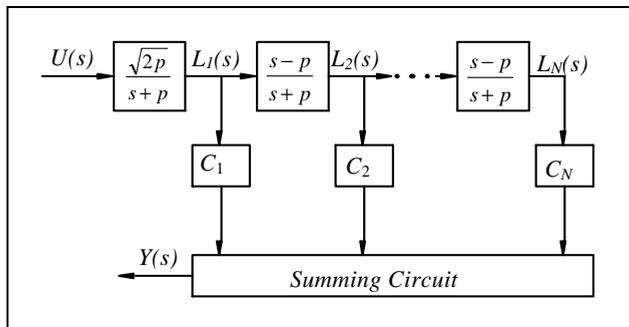


Fig. 1. Laguerre ladder network

This network can be expressed as a stable, observable and controllable state space form as:

$$l(k+1) = Al(k) + bu(k) \quad (4)$$

$$y(k) = c^T l(k) \quad (5)$$

where:

$l(k)^T = [l_1(k), \dots, l_N(k)]^T$ is the state of the ladder (i.e., the outputs of each block in Fig. 1);

$C_k^T(k) = [c_1(k), \dots, c_N(k)]$ are the Laguerre coefficients at time k ;

A is a lower triangular square ($N \times N$) matrix.

The Laguerre coefficients $C(k)$ represent a projection of the plant model onto a linear space whose basis is formed by an orthonormal set of Laguerre functions.

The same concept used in the plant identification is used to identify the process response for measured feed forward variables. For unmeasured disturbances, an estimate of the load is made. This estimate is based on the observation that an external white noise feeds the disturbance model, resulting in a colored signal. The disturbance can be estimated as the difference between the plant process variable increment and the estimated plant model with the integrator removed. Using the plant and disturbance models we can then develop the Model Predictive Control (MPC) strategy.

The discrete state space model used by Zervos and Dumont for the control design takes the (velocity) form:

$$\begin{aligned} \Delta \mathbf{x}_{k+1} &= \mathbf{A} \Delta \mathbf{x}_k + \mathbf{b} \Delta u_k \\ y_k &= y_{k-1} + \mathbf{c} \Delta \mathbf{x}_k \end{aligned} \quad (6)$$

Where u is the input variable, which is adjusted to control the process variable y and \mathbf{x} is the n^{th} -order Laguerre model state. The subscript k gives the time index in terms of number of controller update steps; so the Δ operator indicates the difference from the past update. For example, $\Delta \mathbf{x}_k = \mathbf{x}_k - \mathbf{x}_{k-1}$. The $n \times n$ matrix \mathbf{A} and the $n \times 1$ matrix \mathbf{b} have fixed values derived from the Laguerre basis functions. Values of the $1 \times n$ matrix \mathbf{c} are adjusted automatically during model adaptation to match the process model predictions to the actual plant behaviour. The dimension n gives the number of Laguerre basis functions used in the process model. The algorithm presented here does not suffer from over parameterization of the process model. The BrainWave controller uses $n=15$, which has proven to be enough to model almost any industrial plant behaviour.

Notice that the state equation recursively updates the process state to include the newest value of the manipulated variable. Therefore, we can view the process state as an encoded history of the input values.

Model adaptation may be executed in real time following the recursive algorithm of (Salgado et al, 1988). This algorithm updates the matrix \mathbf{c} according to:

$$\mathbf{c}_{k+1}^T = \mathbf{c}_k^T + \frac{\alpha \mathbf{P}_k \Delta \mathbf{x}_k}{1 + \Delta \mathbf{x}_k^T \mathbf{P}_k \Delta \mathbf{x}_k} (\Delta y_k - \mathbf{c}_k \Delta \mathbf{x}_k) \quad (7)$$

Where the covariance matrix \mathbf{P} evolves according to:

$$\mathbf{P}_{k+1} = \frac{1}{\lambda} \mathbf{P}_k - \frac{\alpha \mathbf{P}_k \Delta \mathbf{x}_k \Delta \mathbf{x}_k^T \mathbf{P}_k}{1 + \Delta \mathbf{x}_k^T \mathbf{P}_k \Delta \mathbf{x}_k} + \beta \mathbf{I} - \delta \mathbf{P}_k^2 \quad (8)$$

\mathbf{I} is the identity matrix. The constants α, λ, β and δ are essentially tuning parameters that can be adjusted to improve the convergence of the adapted Laguerre model parameters \mathbf{C} .

The value of the manipulated input variable u (the controller output) that will bring the process to set point (SP) d steps in the future may be calculated using the model equations. The formula for the process variable d steps in the future is:

$$y_{k+d} = y_k + \mathbf{c}(\mathbf{A}^{d-1} + \dots + \mathbf{I})\mathbf{A}\Delta \mathbf{x}_k + \mathbf{c}(\mathbf{A}^{d-1} + \dots + \mathbf{I})\mathbf{b}\Delta u_k \quad (9)$$

Since it is desired to have the process reach set point d steps in the future, we set $y_{k+d} = SP_{k+d}$ and solve for the manipulated input variable Δu_k .

$$\Delta u_k = \frac{SP_{k+d} - y_k - \mathbf{c}(\mathbf{A}^{d-1} + \dots + \mathbf{I})\mathbf{A}\Delta \mathbf{x}_k}{\mathbf{c}(\mathbf{A}^{d-1} + \dots + \mathbf{I})\mathbf{b}} \quad (10)$$

This equation is the basic control law. As with most predictive control strategies, implementation of the strategy involves calculating the current controller output, implementing this new value, waiting one controller update period, and then repeating the calculation.

Predictive feed forward control can easily be included in this control formulation. A state equation in velocity form is created for the feed forward variable:

$$\Delta \mathbf{z}_{k+1} = \mathbf{A}_{ff} \Delta \mathbf{z}_k + \mathbf{b}_{ff} \Delta v_k \quad (11)$$

Where \mathbf{z} is the feed forward state and v is the measured feed forward variable. The effect of the feed forward variable is then simply added to the output equation for the process variable to become part of the modeled process response:

$$y_k = y_{k-1} + \mathbf{c}\Delta \mathbf{x}_k + \mathbf{c}_{ff}\Delta \mathbf{z}_k \quad (12)$$

Notice that the feed forward state equation creates an encoded history of the feed forward variable in the same way that the main model state equation encodes the manipulated variable.

Re-deriving the control law from the extended set of process model equations yields:

$$\Delta u_k = \frac{SP_{k+d} - y_k - \mathbf{c}(\mathbf{A}^{d-1} + \dots + \mathbf{I})\mathbf{A}\Delta \mathbf{x}_k - \mathbf{c}_{ff}(\mathbf{A}_{ff}^{d-1} + \dots + \mathbf{I})\mathbf{A}_{ff}\Delta \mathbf{z}_k + \mathbf{c}_{ff}(\mathbf{A}_{ff}^{d-1} + \dots + \mathbf{I})\mathbf{b}_{ff}\Delta v_k}{\mathbf{c}(\mathbf{A}^{d-1} + \dots + \mathbf{I})\mathbf{b}} \quad (13)$$

The basic structure of this control law does not change as additional feed forward variables are included in the process model, so it is a simple exercise to include as many feed forwards as necessary into this control law.

Use of the Laguerre process model implicitly assumes that a self-regulating process is to be modeled. In cases where a process exhibits integrating behaviour, it is necessary to modify the Laguerre process model. The modification is two-fold. First, the Laguerre model is altered so that the Laguerre state gives the change in the slope of the process response. That is:

$$\begin{aligned}\Delta \mathbf{x}_{k+1} &= \mathbf{A}\Delta \mathbf{x}_k + \mathbf{b}\Delta u_k \\ \Delta y_k &= \Delta y_{k-1} + \mathbf{c}\Delta \mathbf{x}_k \\ y_k &= y_{k-1} + \Delta y_k\end{aligned}\quad (14)$$

Second, an unmeasured disturbance component is added to the model to estimate the steady state load on the plant. The feedback control law is then derived based on the modified Laguerre model, including the disturbance component.

The above gives the derivation of a d steps ahead adaptive model-based predictive control for a single variable. Full multivariable processes (multiple-input, multiple-output) may also be modeled using Laguerre state-space equations. However, to derive a control law for the multivariable case it is preferable to optimize for a cost function such as the one proposed in the generalized predictive control (Clarke et al, 1987), rather than back calculating the control to achieve a d steps ahead outcome. This concept of predictive control involves the repeated optimization of a performance objective over a finite horizon extending from a future time (N_1) up to a prediction horizon (N_2). Fig. 2 characterizes the way prediction is used within the MPC control strategy. Given a set point $s(k+l)$, a reference $r(k+l)$ is produced by pre-filtering and is used within the optimization of the MPC cost function. Manipulating the control variable $u(k+l)$, over the control horizon (N_u), the algorithm drives the predicted output $y(k+l)$, over the prediction horizon, towards the reference.

The control moves are determined by looking at the predicted future error, which is the difference between the predicted future output and the desired future output (reference). The user can specify the region over which these error values will be summed. The region is bounded by the initial (N_1) and final (N_2) prediction horizon. It is also possible to set the number of control moves that the controller will take to get to the set point by adjusting a parameter called control horizon (N_u). If we weigh the predicted squared error from set point and the total actuator movement with weighting matrices Q and R respectively, and add the two sums, we arrive at the cost function employed within the BrainWave Multivariable controller:

$$J(\Delta u) = \sum_{i=N_1}^{N_2} \|\hat{Y}(i) - \hat{S}(i)\|_Q^2 + \sum_{i=1}^{N_u} \|\Delta U(i)\|_R^2 \quad (15)$$

where $Y(i)$, $S(i)$ and $U(i)$ are the predicted process response, the set point reference and the controller output at update i , respectively. The tuning matrices Q and R allow greater flexibility in the solution of the cost function. The above cost function is optimized with respect to U . By differentiating and solving for U , the next set of optimal control moves is obtained. Input constraints are implemented via a multivariable anti-windup scheme which was proved to be equivalent to an on-line optimization for common processes (Goodwin & Sin, 1984).

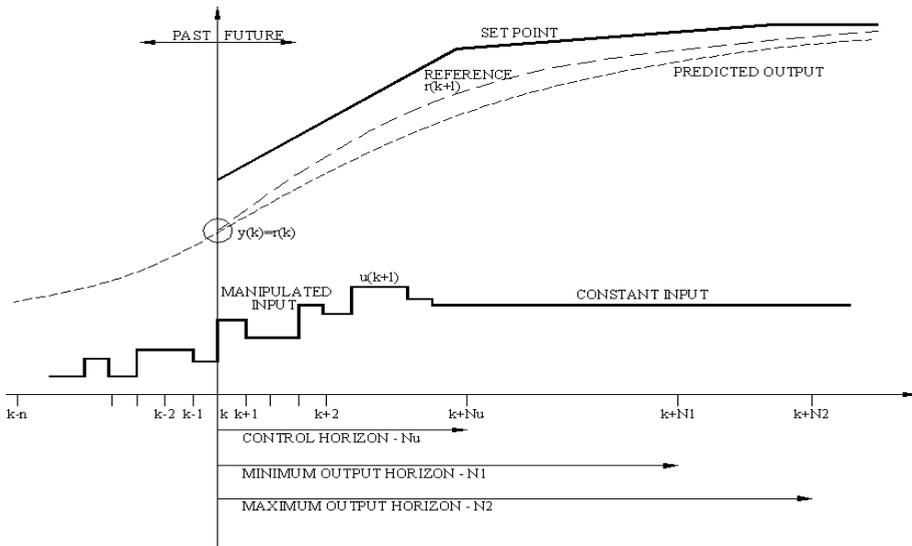


Fig. 2. MPC control concept for multivariable applications

Once the cost function is built, it remains the same until we change one of the models, Q , R , or one of the horizons. At each update, the following takes place: i) the state vector is estimated and adjusted; ii) the process response is estimated, and iii) the next control output is calculated.

Measured disturbances (feed forwards) are assumed to affect one process variable at a time. There can be up to three measured disturbances per process variable in the current controller software structure.

Aside from this change in the derivation of the control law, the multivariable algorithm is substantially the same as the single variable algorithm. That is, a deterministic control law is obtained which provides the current control move that will yield some future process response, the current move is implemented, and then a new control move is calculated based on new process data at the next control update step. For a complete mathematical development of the control law used in the multivariable case, refer to (Huzmezan, 1998).

The controller outlined above has demonstrated more than twenty years of success in industrial applications, verifying the effectiveness of this adaptive model-based predictive control algorithm.

3. Commercial implementation of the BrainWave controller

The BrainWave MPC controller is commercially available as Windows based PC software. The system connects to existing control systems using the OLE for Process Control (OPC) standard interface. A communications watchdog scheme is used to ensure that the process control automatically reverts to the existing control system in the event of any communication or hardware faults associated with the BrainWave computer.

Despite the complex mathematics use in the control and model adaptation algorithms, the software is designed to be easy to use and is suitable for control technicians to apply in an

industrial setting. The user interface for the BrainWave system is shown in Fig. 3. The interface includes a trend display of the process variables at the top right side of the interface. In this example, the set point is the yellow line, the process variable is the red line, and the controller output (the actuator) is the green line.

The identified process transfer function is shown on the lower right side. The transfer function plot is generated based on a step input at time=0 and thus shows the open loop transient response of the process to a change in the actuator or measured disturbance variable. The white line is a plot of the estimated transfer function of the process (expressed as a simple first order system using a dead time, time constant, and gain) which is used as a starting point for the model identification. The red line is a plot of the identified process transfer function open loop step response based on the Laguerre representation. The blue bars represent the relative values of the 15 Laguerre coefficients which are the identified process model parameters.

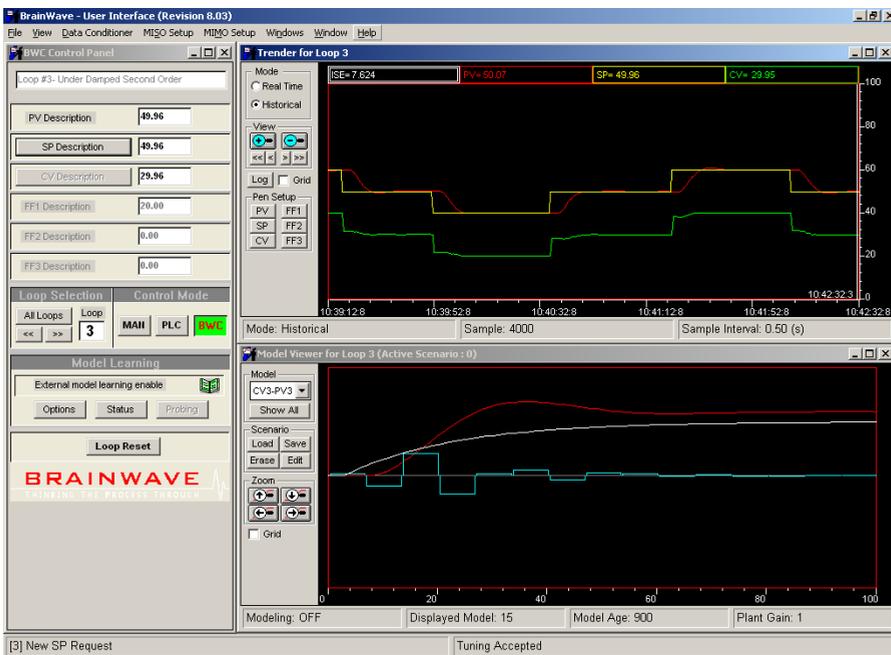


Fig. 3. BrainWave user interface

BrainWave allows the user to configure single loop controllers (Multiple Input Single Output – MISO) and multivariable controllers where more than one control loop interacts with other control loops (Multiple Input Multiple Output – MIMO). The process type is chosen as either self-regulating for stable systems or integrating for open loop unstable systems such as level controls. The primary information required is an initial estimate of the process response. This is entered using a simple first order plus dead time transfer function estimate. This estimate is used by BrainWave to determine the appropriate data sample rate for modeling and control of the process and also provides a starting point for the initial Laguerre model of the process.

Many systems are well described using the simple first order model estimate, and if the estimate is reasonably close to the actual process response, the BrainWave controller will be able to assume automatic control without any further configuration work. The default setup parameters are set to values that will provide a closed loop response time constant that is equal to the open loop response time constant of the process, thus providing effective and robust control without any additional tuning required.

Multivariable MIMO systems can be configured with a dimension of up to 48 inputs and 12 manipulated outputs. Estimates of the response of each process variable to each actuator or disturbance variable must be entered (if the cross coupling between the respective channels exists) so the complete array of process transfer functions is shown as a matrix.

For MIMO systems, it is desirable to be able to place more priority on one process variable than another as part of the controller setup. Similarly, some actuators are able to move more quickly compared to other actuators. The MIMO control setup provides simple sliders that allow the user to impose these preferences on the controller in a relative fashion between the process variables and actuators. Note that the default settings provided will result in stable and robust control of the process where the closed loop response time constant is equal to the open loop response time constant for each process variable.

3.1 Model identification

The BrainWave controller has online modeling features that help the user obtain the correct process transfer function model for the process. The model identification can be performed in open loop by observing the process response to manual changes to the actuator(s) or in closed loop during automatic control in BrainWave mode. Performing the model identification in closed loop is advantageous as it allows the user to confirm the improvement in the control performance at the same time as the convergence of the identified model is monitored in the model viewer, thus providing real-time confirmation that the identified process model is correct.

An example of the model identification procedure is shown in Fig. 4. The user starts by entering an estimate of the process response in simple first order terms as described earlier (the white line shown in the Model Viewer panel). BrainWave builds a Laguerre model that matches this estimate and uses this model as a starting point for both the predictive control operation and the model identification (the red line in the Model Viewer panel). A series of set point changes are made while the BrainWave controller is in control of the process as shown in the Trend display panel. Some overshoot is apparent during the first set point change due to the errors in the initial process response estimate provided by the user. As the series progresses, the identified process model converges to the correct value. As the model becomes more correct, the control performance during each successive set point change is improved. At the end of the sequence, the process model is completely converged to the correct value, and the resulting control performance is ideal.

Feed forward disturbance variables can also be modeled automatically while BrainWave is in control of the process. This unique capability allows the controller to identify the transfer function of the disturbance variable to the process so that the controller can calculate the correct control move with the actuator to cancel the predicted disturbance on the process. This feature enables BrainWave to provide the best disturbance cancellation possible. An example of the adaptive disturbance cancellation capability is shown in Fig. 5. The feed forward variable is the square wave signal at the bottom of the figure. In this example, the

BrainWave controller begins with no model for the feed forward disturbance variable so the process is disturbed from the set point and the actuator (the trend in the center of the figure) reacts by feedback after the disturbance has already occurred to return the process to the set point. As the feed forward transfer function is identified by BrainWave, the controller begins to take immediate action when the feed forward disturbance signal changes, thus providing improved cancellation of the disturbance. As the identified feed forward model converges to the correct value, the cancellation of the disturbance is complete.

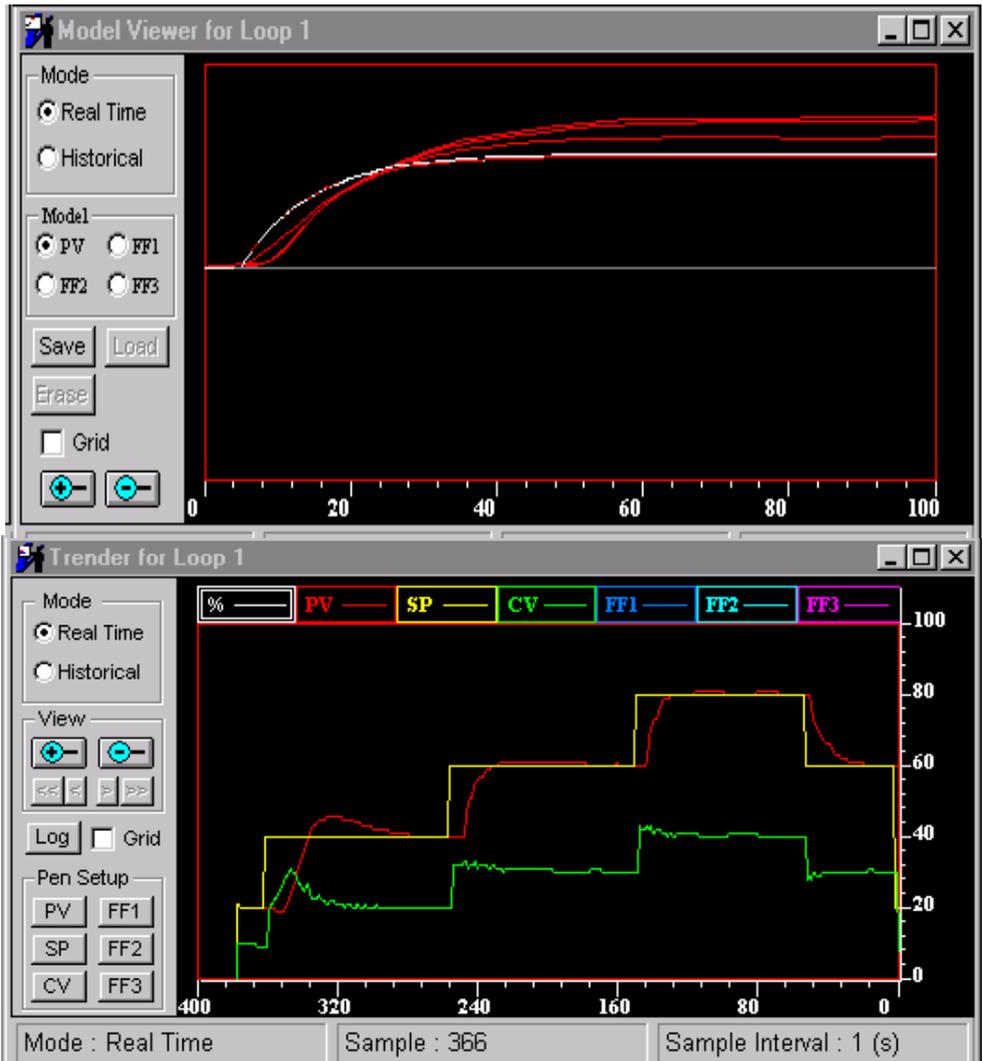


Fig. 4. Process model identification during closed loop control

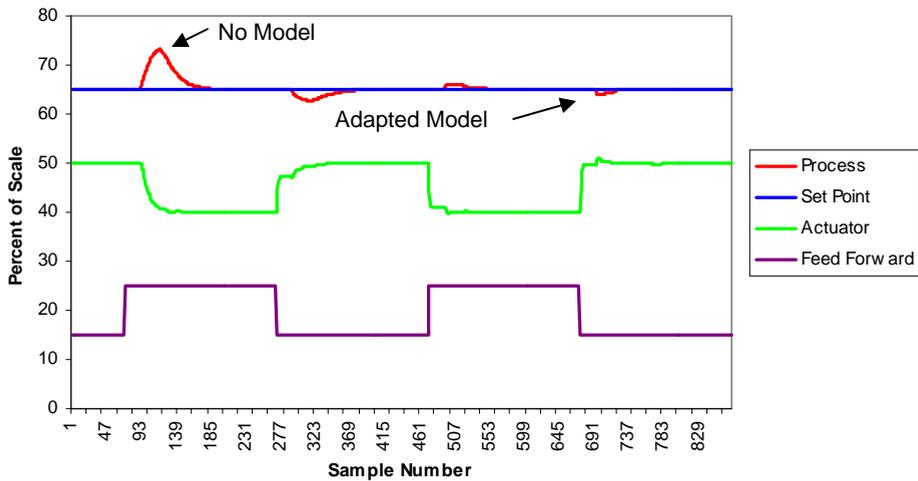


Fig. 5. Adaptive feed forward disturbance cancellation

3.2 Predictive control

The identified process model is used as the basis to calculate the required control moves with the actuator to bring the process to the set point some time in the future. For the single loop MISO controller, the primary adjustment for control performance is the prediction horizon. This is essentially the number of control steps into the future where the process variable must be on the set point. A long prediction horizon results in conservative closed loop control response; the actuator is simply positioned to the new calculated steady state value and the process reaches the set point according to its natural open loop response time. Shorter prediction horizons cause the controller to make a more aggressive transient move with the control actuator in order to bring the process to the set point in less time than the natural response. Fig. 6 shows the effect of adjusting the prediction horizon for self-regulating (open loop stable) systems.

Fig. 7 shows the effect of adjusting the prediction horizon for integrating (open loop unstable) systems. In addition to adjusting the prediction horizon, the set point reference is also internally filtered to provide less aggressive actuator movement during set point changes. It should be noted that integrating systems are only stable in closed loop for a certain range of controller behavior (a marginally stable system in closed loop) so the amount of arbitrarily fast or slow control performance adjustment is limited.

In the multivariable MIMO controller, there are several parameters that can be adjusted to change the control performance. The weighting can be adjusted to change the penalty for set point tracking error for each process variable and the movement penalty for each actuator. The control horizon, which specifies the number of future control moves to be calculated, can be made longer for conservative actuator movement and slower process response or shorter for more aggressive actuator movement and faster process response. The prediction horizon is also adjusted to determine the range of future process response that will be included in the cost function minimization. Typically this range begins some time after the

process with the longest time delay has elapsed and ends where the process variables should naturally arrive at steady state. As there are many parameters that have a similar effect on the control performance, typically most are set to their default values and only the set point tracking error weightings are used to adjust the relative priority of the process variables being controlled.

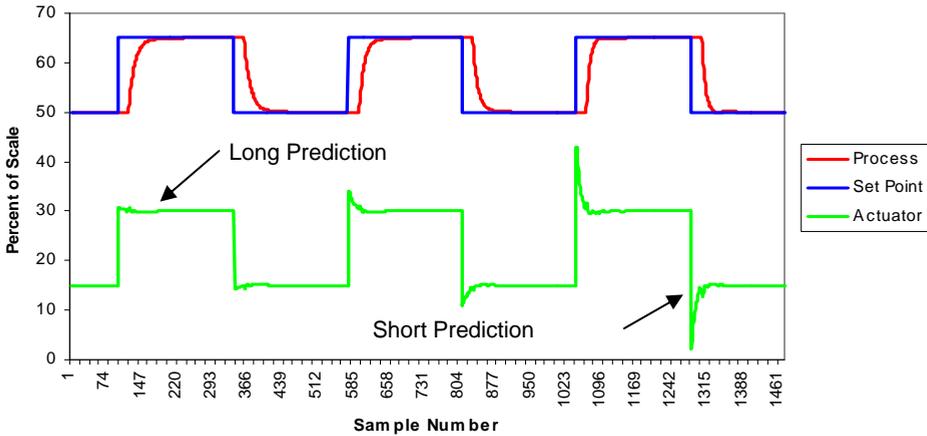


Fig. 6. Effect of Prediction Horizon Adjustment for Self-Regulating Systems

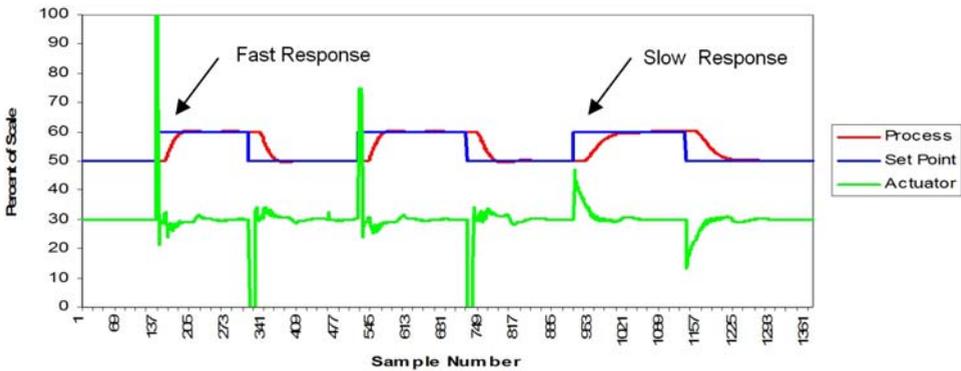


Fig. 7. Effect of prediction horizon and set point reference filtering for integrating systems

4. Mineral processing applications

Mineral recovery processes are notoriously difficult to control due to a combination of factors, including variable ore properties, complicated process dynamics, interacting process variables, and an inability to measure some key variables. Considerable time and effort has been put into the development, installation, tuning, and testing of automation systems for

mineral recovery plants due to the high value of the process. A typical approach is to use PID controllers, with enhancements such as cascade control, feed forward control, ratio control, and so forth, that are available in distributed control systems (DCS). It is possible to have some degree of success in automating and bringing stability to processes with these techniques; however, PID does not perform well when there are challenging loop dynamics (such as the transport delay associated with ore feed systems, or the integrating behaviour of flotation cell levels), or multiple interacting variables (such as rotation speed, recycle flows, and ore feed rate on SAG mill weight).

A more advanced approach to automation that seems to be popular among mineral processors is the use of rule-based expert systems. A rule-based expert system that mimics the best operator actions is a logical development towards solving underlying difficult feedback control problems in the absence of other alternatives to PID control. A number of these rule-based expert systems are commercially available and they typically take the form of software running on a PC that is frequently exchanging information (receiving process data and sending control outputs) with the DCS. However, in simply trying to automate the actions of even the best human operators, there is the potential to miss an opportunity to make a full step improvement in the control of the process. For example, MPC can provide control performance improvements by managing the process dynamics and interactions in a completely different manner.

MPC is able to provide a quality of regulatory control that cannot be matched by PID control or expert system control. The superior performance of MPC in controlling challenging loops provides a clear benefit in terms of plant profitability. It is not effective to replace this advanced regulatory control layer by trying to extend traditional DCS-based controls upwards, or expert system type controls downwards; so without the advanced regulatory control layer with MPC, a comprehensive plant automation strategy cannot be properly built.

4.1 SAG mills

A semi-autogenous grinding (SAG) mill is a rotating cylinder containing steel balls that is used as an intermediate stage in the comminution (size reduction) of ore. Typically, these mills receive ore from a primary stockpile and, operating continuously, reduce the particles to a size appropriate for finer grinding in ball mills. As the name indicates, size reduction in a SAG mill occurs both from the tumbling action with the balls and from autogenous (rock on rock) grinding.

SAG mills are a critical component in mineral processing operations as they are often the bottleneck of the processing line; at the same time, they are a difficult process to control due to the transport delay inherent in the ore feed system and the integrating nature of the mill as it approaches maximum load. Depending on a number of factors, the weight of material resident in the mill will vary. It is important to maintain the weight within a specific range, as an overloaded mill quickly loses grinding efficiency, while an insufficiently loaded mill does not take proper advantage of the autogenous grinding mechanism. Grinding is also affected by rotation speed; in general, greater rotation speed allows for increased grinding. Finally, the power draw of the mill must be monitored to avoid exceeding the maximum power limit. Although brief, this description of mill operations begins to indicate the complex, multivariable nature of the SAG mill control problem.

A very direct, and popular, approach to maximizing mill throughput is to use an expert system to gradually increase the feed rate to the mill until a high limit for weight or power

draw has been reached. Should a high limit be violated, feed rate to the mill is reduced until mill operations return to acceptable limits. This approach has the advantage of being direct and easy to understand, but can result in a 'saw tooth' pattern of feed rate increases and decreases, which may not be desirable. The area below this saw tooth pattern represents an opportunity to achieve higher average ore feed rate and throughput.

An alternative to this approach is to adjust mill feed rate to maintain mill weight at a set target. The idea justifying this approach is that there is a mill weight at which optimum grinding occurs. Therefore, by maintaining the correct mill weight, mill throughput is maximized. This approach has the benefit of increasing the stability of mill weight (and power draw). The drawback to this approach is that it is not always clear what weight target should be chosen, although adjusting the weight target to maximize power draw may complete this strategy.

Enhancements to these strategies may include the use of feed particle size distribution, ore hardness, and ore type as predictors for mill grinding efficiency. Mill sound may also be used as an indicator of the tumbling profile inside the mill. Some strategies have attempted to control the mill sound by adjusting mill rotation speed; however, this can be problematic due to the large and rapid effect that rotation speed can have on mill weight.

The adaptive model-based predictive control strategy based on the BrainWave MPC controller has been applied to a number of SAG mills in primary copper producing mines. The mills had a range of capacities, with the smaller mills operating at ore throughputs as low as 40,000 tons per day, and the larger mills operating at 120,000 tons per day or more.

The typical application of the BrainWave controller for SAG mills is for control of the mill load. In these cases, mill load was inferred either from a direct weight measurement or from bearing oil pressure. Fig. 8 gives a diagram showing the SAG Mill and the load control strategy. The mass feed rate of ore is measured on the feed belt and typically an enhanced PID control strategy is used to control the ore feed rate. BrainWave operates as a master controller over the feed rate controller. This controller takes the load measurement and set point, as well as key feed forward variables such as mill rotation speed, pebble recycle rate, and ore sizing information (coarse or fine fraction) and sets the set point for the feed rate controller. In some cases the BrainWave MPC may also be used for the feed rate control itself. Where there is significant transport delay between an increase in the addition of ore to the feed belt and the measurement of that feed rate increase, MPC can provide improved feed rate control.

It should be noted that in the majority of cases, this strategy was implemented on SAG mills that were already operating with expert system control. In these cases, BrainWave was integrated with the expert system, taking over the task of setting the feed rate to the mill.

The results of the MPC application demonstrated increases in mill throughput in the range of 1.5 to 2% relative to mill throughput with expert system control alone. Table 1 lists some results. To emphasize the significance of these increases, note that for a concentrator processing 120,000 tonnes per day of ore at a grade of 0.75%, with a recovery of 0.85, total annual copper production is roughly 550 million pounds. Even at a low profit margin of \$0.20/pound, a production increase of 1% is worth over one million dollars of additional profit per year.

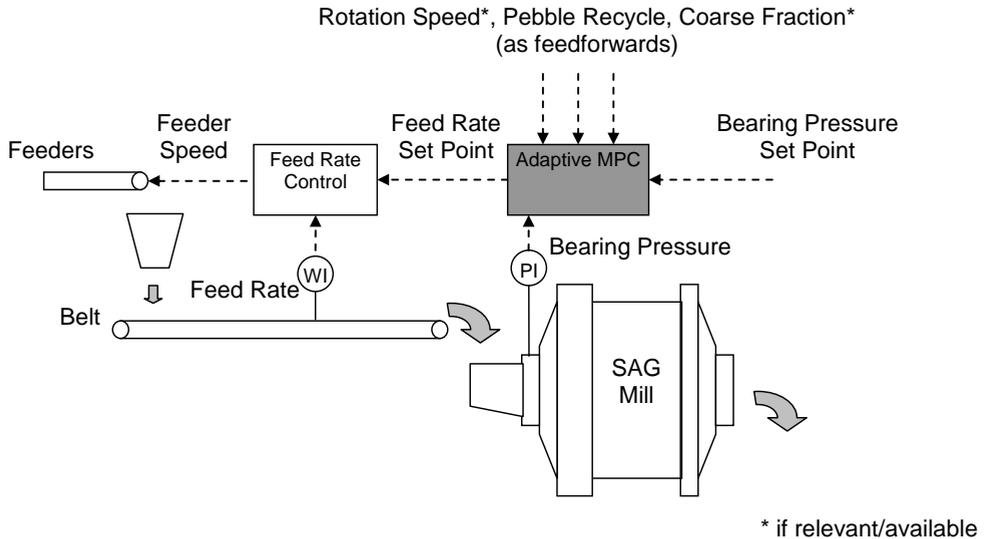


Fig. 8. BrainWave SAG mill load control

Mine Site	Number of SAG Mills	Production Increase
Minera Candelaria	2	1.6%
Minera Escondida – Laguna Seca	1	>2%
Minera Los Pelambres	2	1.5%

Table 1. SAG Mill Throughput Increases with MPC

Fig. 9 displays some process trend data from one of the applications over a period of several days. The trend also shows that when the MPC was taken off-line for some hours for maintenance the expert system was not able to maintain the mill load with the same stability (circled region in the trend plot). This particular concentrator plant is fed with a mixture of two ore types with significantly different work indexes. For this reason, grinding rates in the mill appear to change frequently and rapidly and the MPC control proved to react sooner and minimized the disturbances caused by these events. The impact of using MPC on overall mill performance was shown to go far beyond stabilization of mill load. One plant site observed reductions well above 50% in the standard deviation of ore feed rate, mill rotation speed, mill weight, and mill power draw.

4.2 Flotation cells

Mineral flotation is a process that takes advantage of differences in hydrophobicity to separate valuable minerals from tailings or one valuable mineral from a bulk concentrate. Hydrophobic ore particles become attached to air bubbles which rise to the top of the flotation cell to form a froth layer. The froth is collected as it overflows the top of the cell while the rest of the material passes through the cell outlet. Typically, a number of cells are arranged in series so that as the pulp flows through a flotation line, the hydrophobic particles have a number of opportunities to separate from the pulp.

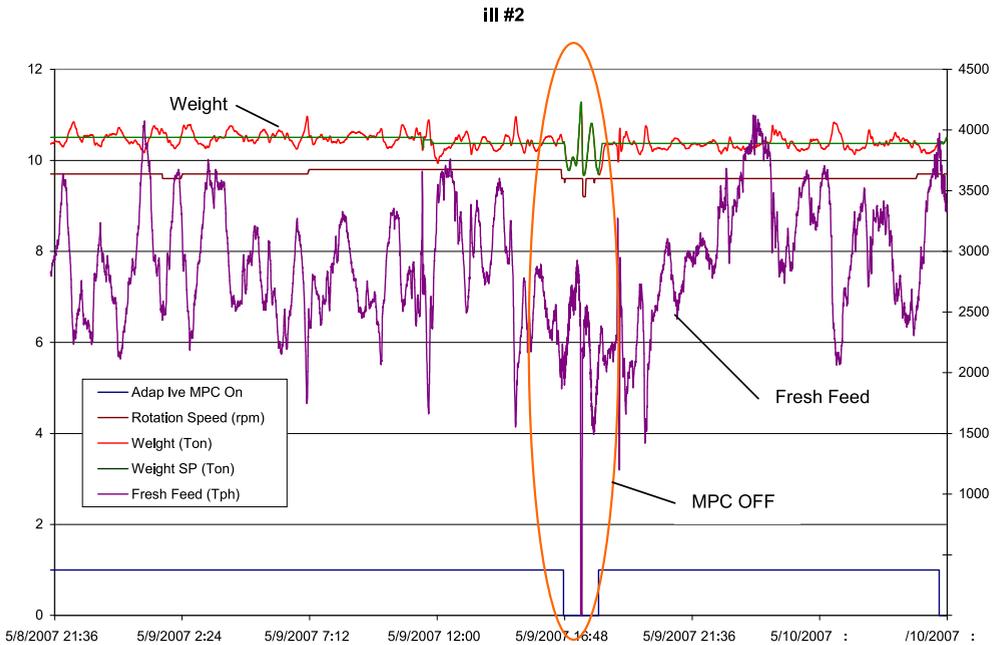


Fig. 9. BrainWave control of SAG mill load

To promote the success of flotation, it is important to have good control of the froth depth. Commonly, froth depth is inferred by measuring the location of the froth-pulp interface (with a float device) relative to the lip of the cell where the froth is able to spill into the recovery system. Under normal cell operations, froth will completely fill this space, from the top of the liquid level in the cell up to the lip of the cell. If the froth level can be maintained, a stable froth layer is formed without excessive bubble breakage, and there is a steady overflow of froth over the lip of the flotation cells. A well-chosen froth depth allows time for some 'drainage' of entrained water and tailings particles before the froth overflows the cell; however, greater froth depths can result in lower recovery and increased use of expensive frother chemicals (Wills & Napier-Munn, 2006).

Froth level control can be a challenging problem for a number of reasons. There can be large and sudden changes in the flow of pulp into the flotation line. Often this flow is unmeasured and the changes can cause large level disturbances. The arrangement of a number of flotation cells in series means that the outlet flow from one cell is the inlet flow to the next cell in the line. Therefore, as outlet valve position is adjusted to control cell level, the levels in downstream cells will be affected. The valves used in flotation applications are often dart valves or pinch valves that may not always have a fast and accurate positioning response. To summarize, control of flotation level is difficult due to the combination of significant unmeasured process disturbances, interacting process variables and imperfect actuators.

BrainWave MPC was applied to two copper rougher-scavenger flotation lines, each consisting of five 160 m³ flotation cells. Each cell level is controlled by an individual controller which adjusts the cell's outlet valve position. To compensate for the impact of valve position changes on downstream cell levels each level controller takes the upstream cell's outlet valve position as a feed forward disturbance variable. This allows each

controller to minimize disturbances by adjusting outlet valve positions at the same time as the inlet valve positions are changing. Fig. 10 provides a simple diagram illustrating the application of the control loops.

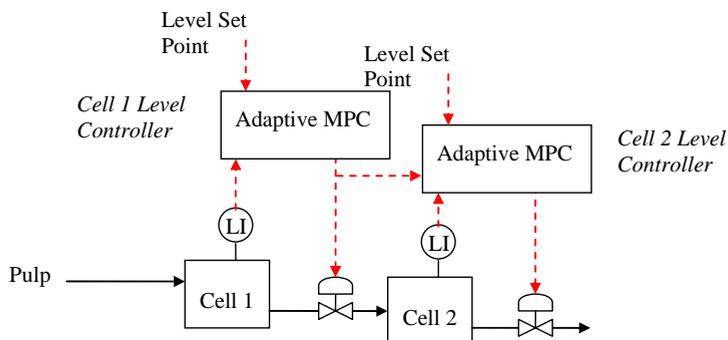


Fig. 10. Diagram of flotation control strategy

The advanced control loops replaced the existing PID loops which the plant had previously used to maintain cell level. The PID controllers had struggled to maintain tight control and had particular difficulty stabilizing the cells after large disturbances or on plant start-ups. Fig. 11 demonstrates the improvement to the cell level control that was achieved by replacing traditional PID loops with the BrainWave loop controllers. In this case there was as much as 60% reduction in level variability as measured by standard deviation.

It is suggested that improved level stability has the effect of improving mineral recovery, improving product grade, and reducing frother consumption. However, these are difficult benefits to prove, due to the problem in obtaining and collecting sufficient data, where the comparisons can be made given the same operating conditions (for example, with the same production rates and ore types). Unfortunately, to date, the plant has not been able to complete such an analysis. However, one obvious and easily measurable benefit came from the improved control performance on large production rate changes or plant start-ups. It was observed that the PID controllers had difficulty in stabilizing the cells after these events; often cell levels could swing for as much as two hours before settling into what could be considered steady-state. This settling time was greatly reduced with the BrainWave controllers. The benefits from avoiding this loss in operating time can be directly calculated. An example calculation can be made based on the business fundamentals given in Table 2.

Tonnes Milled per Day	50,000
Copper Grade	0.3%
Recovery	75%
Tonnes Copper Produced	112.5
Pounds per Metric Tonne	2,205
Price per Pound	\$4.00
Production Cost	\$1.50
Daily Profit	\$620,156

Table 2. Example Mineral Concentrator Business Fundamentals

If the BrainWave control reaches ‘steady state’ in one hour less than PID control, and there is one of these large disturbances events per week, then this represents the equivalent of 2.2 more days of operating time per year. Based on daily revenue of \$620,156, this gives an increase in profit of \$1.36 million annually.

Note that this is only the ‘easily’ calculated benefit and does not include the additional benefits to be obtained through improvements in recovery. Even a modest 0.5 percentage point increase in recovery from improved froth level control yields close to an additional \$1.1 million per year in profit.

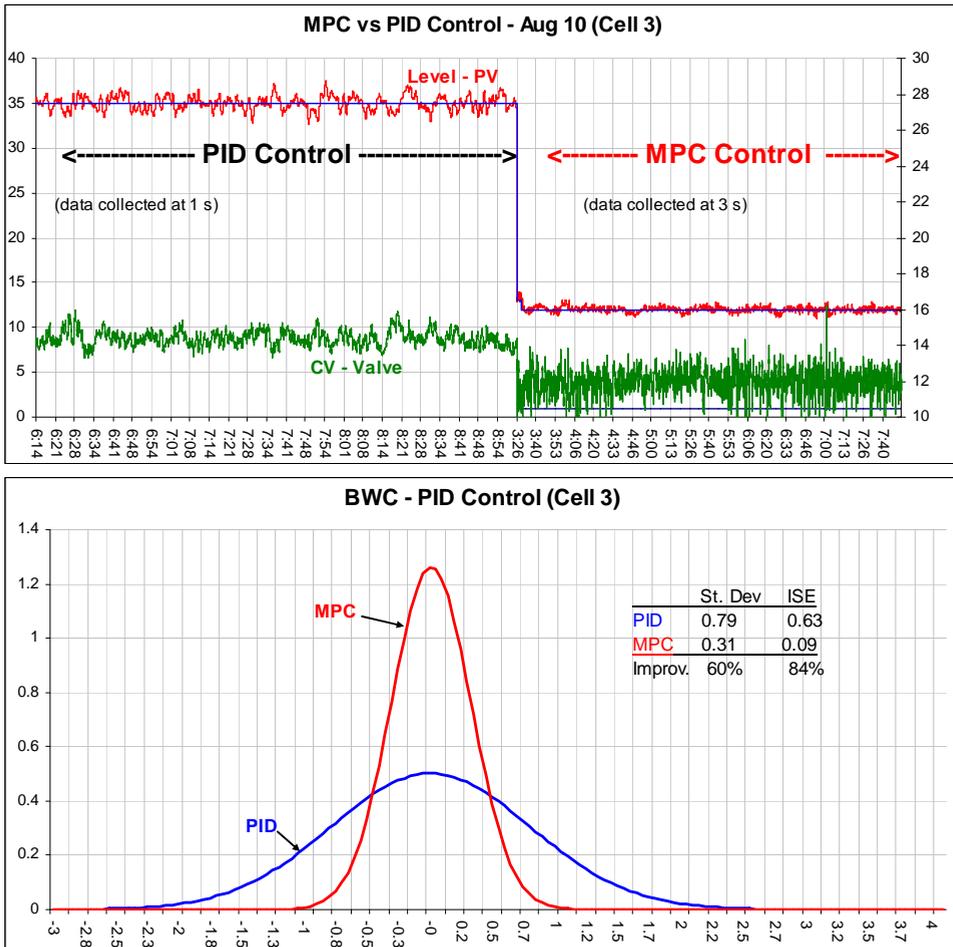


Fig. 11. Comparison of PID and BrainWave control of flotation level

5. Pulp and paper applications

Many processes involved in the manufacture of pulp and paper exhibit challenging dynamics for control due to long reaction times. The pulp digester, which cooks the wood chips with

digester is controlled by adjusting the flow of chips from the impregnation vessel (sluice flow) into the digester, which is fed at the top of the column. Transport delay time as well as delays in the digester level measurement, combined with the integrating level response, create a difficult control problem.

The existing digester level control was based on a PID controller in the DCS. During large disturbances, the operator assumed manual control to try and stabilize the level. The BrainWave controller was able to reduce the standard deviation of the level by more than 50% and required much less intervention from the operator. Fig. 13 provides a comparison of the control performance when using the existing DCS/Manual control approach and the improved control achieved with BrainWave.

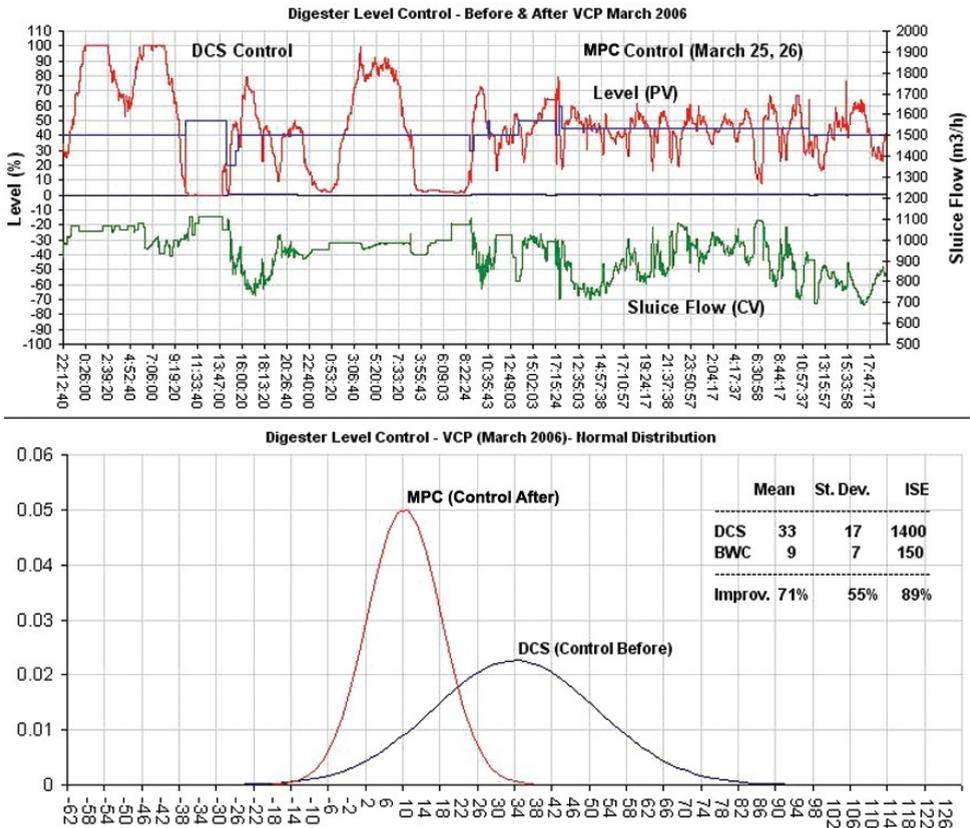


Fig. 13. Comparison of MPC vs. DCS control of digester level

5.2 Lime Kiln control

The lime kiln is used to convert calcium carbonate into calcium oxide (lime) for use in the recaustification process that converts sodium carbonate to sodium hydroxide for use in the digester. The properties of the lime are dependent on the temperature profile of the kiln. The temperature profile is typically manually controlled due to the long time delays and

multivariable interactions of the draft (air flow) and fuel on the kiln temperature profile that make automatic operation with conventional PID controllers impractical. Response times of one to three hours or more are typical. Operators are often impatient with the long response time of this system and tend to make large corrections to the fuel feed rate in an attempt to recover the temperature profile quickly during process disturbances such as production rate changes. These actions result in extremes of temperature in the kiln, leading to poor lime quality, ring formation problems, and reduced refractory life. Operators also tend to control the temperature profile at a higher value than necessary for the lime burning and at a high excess oxygen level to provide a comfortable operating margin that requires less frequent attention. These practices lead to increased fuel consumption and maintenance costs.

Adjusting draft and fuel cause shifts in the flame length and excess oxygen levels. In addition to the long response times, this interaction must also be addressed by the control strategy to achieve responsive yet stable control performance. The ultimate objective of the control strategy is to maintain a constant lime discharge temperature to ensure consistent lime quality as measured by the residual calcium carbonate (un-burned lime) and reactivity with water to produce calcium hydroxide (slaking rate).

A multivariable MIMO BrainWave controller is used to control the temperature and oxygen level at the feed end of the kiln by adjusting the fuel and induced draft (ID) fan. A single loop BrainWave controller is used to control the lime discharge temperature by adjusting the target for the feed end temperature. This approach allows feed end temperature limits to be easily included in the control strategy, as low temperatures can lead to plugging of the lime mud feed and high temperatures can lead to equipment damage in the dust removal system. A schematic of the control scheme is given in Fig. 14.

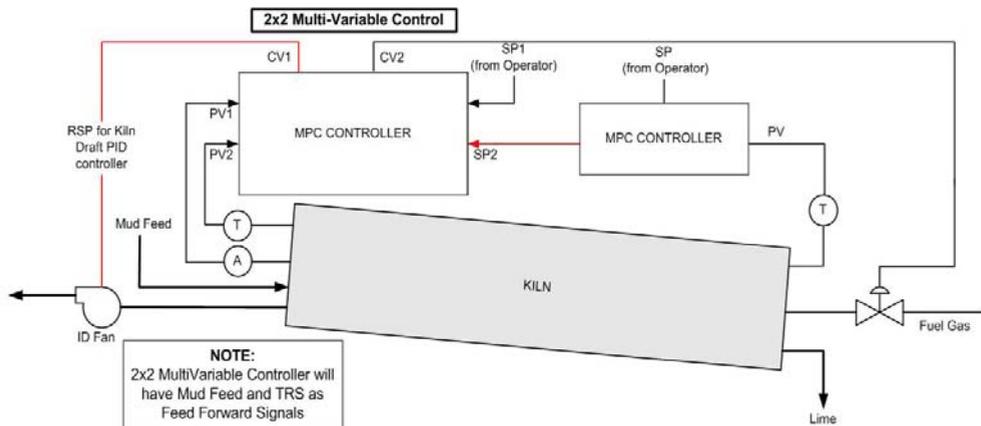


Fig. 14. Lime Kiln control scheme

A chart of the feed end temperature, oxygen level, and firing end temperature is shown in Fig. 15 for both manual control and automatic control with BrainWave. A summary of the performance improvements obtained by the BrainWave MPC controller on this application is shown in Table 3. The range of variation of each process variable was substantially reduced, allowing the kiln to operate at a lower average temperature with lower excess oxygen. These improvements resulted in reduced fuel consumption, reduced incidence of

ring formation, increased production capacity, and a better quality lime (as measured by residual Calcium Carbonate CaCO_3) as shown in Fig. 16. Based on the results of this application, as well as experience with over 20 other similar applications, the control improvements possible with MPC provide reductions in fuel consumption of 5% or more while reducing lime quality variability by 50%.



Fig. 15. Lime Kiln control comparison

Process Variable	Manual Control	MPC Control	Improvement
Excess Oxygen	1%	0.3%	70%
Feed Temperature	40°F	7°F	82%
Lime Temperature	200°F	25°F	87%

Table 3. Lime Kiln process variability comparison

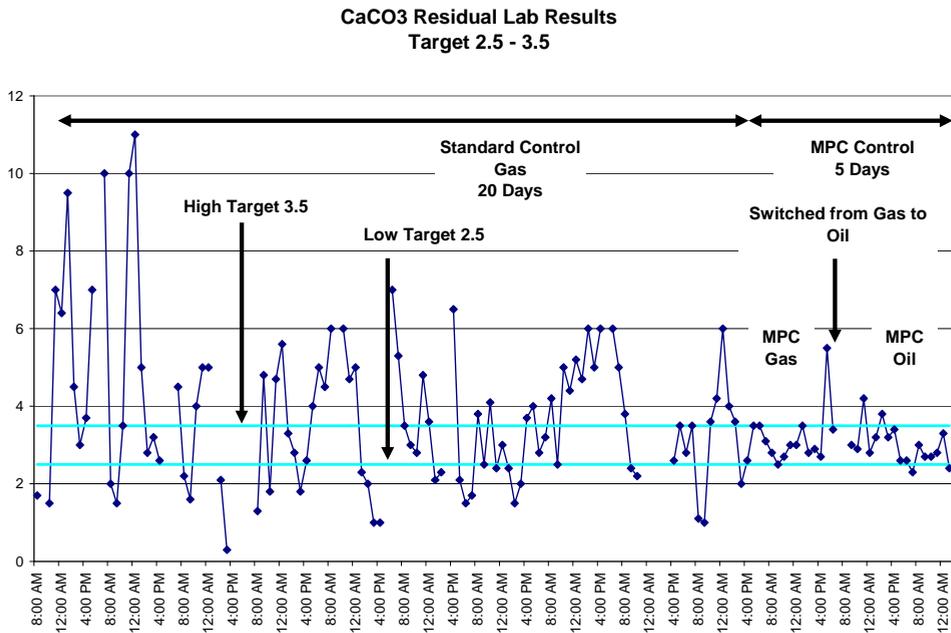


Fig. 16. Lime Kiln CaCO₃ residual laboratory results comparison

5.3 Pulp bleaching

The pulp bleaching process consists of several stages where bleaching chemicals are applied to the pulp to increase brightness. These reactions occur in large towers with plug flow of the pulp to allow long retention time for completion of the bleaching reaction. One of the stages in the bleaching process is known as extraction stage where sodium hydroxide is applied to the pulp to remove remaining lignin that was not removed in the digester. The addition rate of the sodium hydroxide is controlled based on the pH at the exit of the extraction stage as this measurement provides an indication if the correct amount of chemical was applied. High pH values indicate that excess chemical was applied and can result in damage to the pulp fibers and loss of pulp quality. Low pH values indicate that insufficient chemical was applied resulting in less removal of lignin. The higher lignin content will require additional expensive bleaching chemicals in the downstream stages in order to achieve the target final pulp brightness.

Control of extraction stage after tower pH is challenging due to the long and varying dead time, and that fact that the dead time and the process gain change significantly with production rate. Due to the plug flow nature of the reaction tower, the process dead time for the pH control is five times longer than the process time constant, making this control application particularly difficult. The pH response to a change in addition rate of sodium hydroxide had about two hours of dead time and a time constant of about 17 minutes.

As production rate changes affected these process dynamics significantly, the BrainWave MPC controller was configured with a set of process models to cover the entire production range. The main differences between the models were the process gain and dead time. Process gain ranged from 0.6 to 2.0 and dead time ranged from 2,000 to 6,000 seconds.

Lower production rates will require models with higher gain and longer dead time. As production rate increases, model gain and dead time will decrease. The MPC controller dynamically loaded the appropriate model according to the production rate as this provides a faster solution in this case than relying on adaptation alone to correct for the changes in the process. The mill had attempted to implement a Dahlin type controller but they had difficulty keeping the process stable. The addition rate of sodium hydroxide was applied as a ratio to the pulp production rate and the operator manually adjusted this ratio to maintain the extraction pH in the correct range.

Fig. 17 shows the control performance achieved by the operator and the MPC control. Table 4 shows the comparison between the MPC control and manual control. The improved control stability provided by the MPC control allowed operation at an average pH set point of 10.2 instead of 10.5, resulting in a reduction of sodium hydroxide addition with corresponding savings of about \$100,000 per year.

Performance Index	Manual Control	MPC control	Improvement
Standard Deviation	0.089	0.032	64%

Table 4. E Stage pH control improvement summary

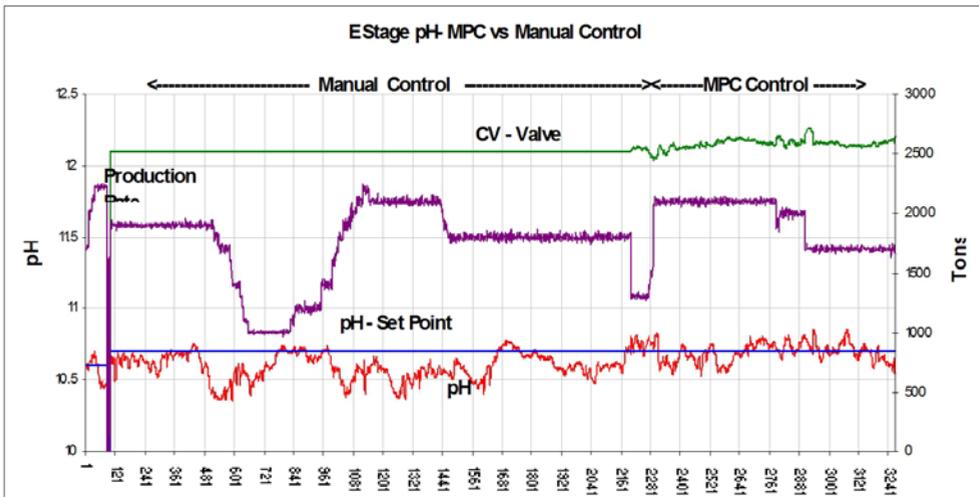


Fig. 17. Extraction stage pH control comparison

5.4 Pulp dryer control

Pulp dryers are used to control the final moisture content of the pulp before it is shipped. The moisture must not exceed a maximum specification limit so the dryer tends to be operated with slightly over-dry pulp. This energy required for pulp drying can be reduced if the pulp moisture can be controlled as close as possible to the specified limit. BrainWave MPC is ideally suited to control the drying process due to its ability to account for the long transport delay time as the pulp moves through the dryer to the moisture measurement sensor located at the dryer exit. The MPC controller also provides an effective means to incorporate measured disturbance variables such as sheet speed, broke flow, and pulp consistency as feed forward signals.

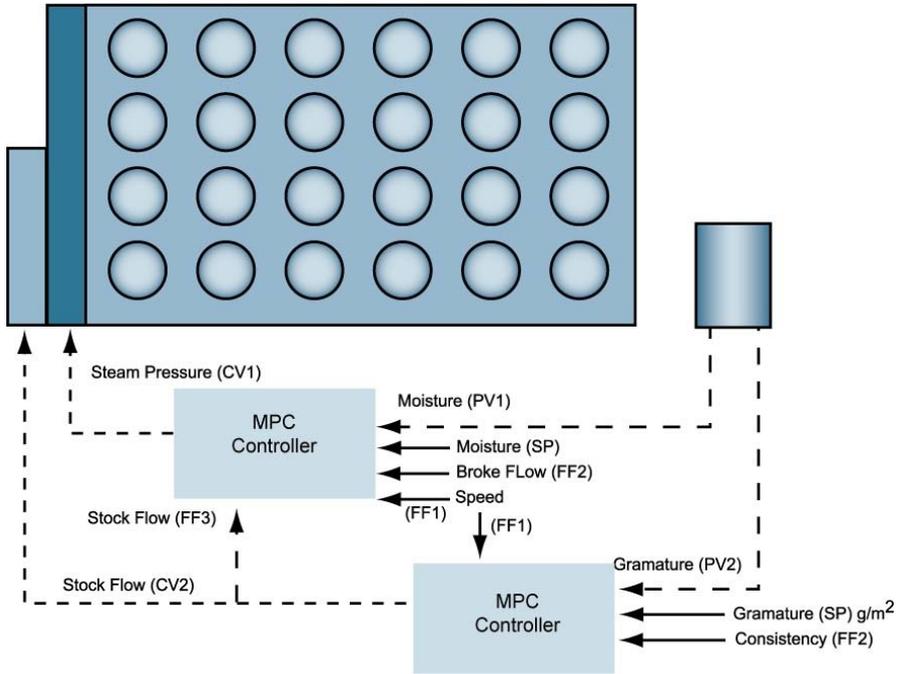


Fig. 18. Pulp dryer control scheme

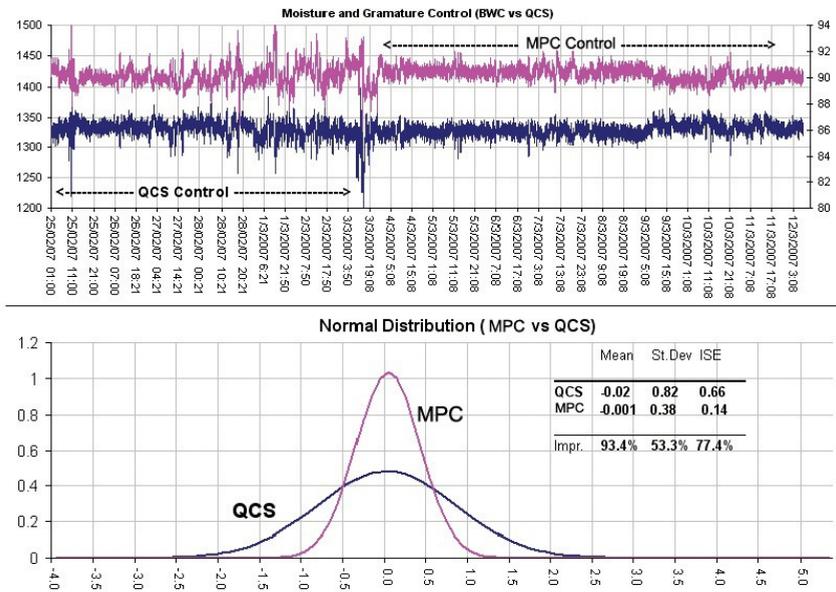


Fig. 19. Pulp dryer control performance comparison

In addition to pulp moisture control, MPC was also used to control the pulp gramature (mass of pulp per square meter) in the mat forming section at the feed end of the dryer. A diagram of the pulp dryer control schematic is shown in Fig. 18. The pulp gramature is controlled by adjusting the flow rate of pulp stock onto the wire section that forms the pulp mat. The final pulp moisture is controlled by adjusting the steam pressure applied to the dryer sections.

In this example, the pulp dryer was part of a new pulp mill and was one of the largest pulp dryers ever built. The existing Quality Control System (QCS) was used to control the pulp moisture and gramature before the BrainWave MPC was installed. A comparison of the moisture and gramature control performance is shown in Fig. 19. Standard deviation of the pulp moisture and gramature was reduced by more than 50% compared to the QCS system. With the improved stability, the average pulp moisture could be kept closer to maximum, leading to increased production and energy savings.

6. Conclusions

In this chapter, the development and application of a Model Predictive Controller (MPC) has been presented. It is clear that many industrial processes cannot be adequately controlled using conventional Proportional-Integral-Derivative (PID) control techniques due to common problems such as time delay and multivariable interactions. MPC exploits the abundance of inexpensive computing power that is now available so the limitations of the old pneumatically powered PID approach can be eliminated. MPC provides an opportunity to improve the performance of most industrial processes in order to reduce production costs and environmental impact, and improve product quality and profitability. These improvements can be achieved much faster and at less capital cost compared to modifications or upgrades of the process equipment resulting in an attractive return on investment.

7. Acknowledgements

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