Time Delay Integrating Systems A Challenge For Process Control Industries A Practical Solution

Mihai Huzmezan [a] William A. Gough [c] Guy A. Dumont [b] Sava Kovac [d]

[a] *University of British Columbia, Electrical and Computer Engineering, 2356 Main Mall, Vancouver, BC, Canada, V6T 1Z4, huzmezan@ece.ubc.ca*

[b] *University of British Columbia, Electrical and Computer Engineering, 2356 Main Mall, Vancouver, BC, Canada, V6T 1Z4, guyd@ece.ubc.ca*

[c] *Universal Dynamics Technologies Inc., # 100 - 13700 International Place, Richmond, BC, Canada, V6V 2X8, bgough@udtech.com*

[d] *Universal Dynamics Technologies Inc., # 100 - 13700 International Place, Richmond, BC, Canada, V6V 2X8, skovac@udtech.com*

Abstract

Temperature control of processes that involve the heating and cooling of a closed batch reactor can be a real problem for conventional Proportional-Integral-Derivative (PID) based loop controllers. This paper describes the application of a new industrial advanced process controller. This controller is designed to handle integrating type processes with long dead times and long time constants. The results demonstrate that reactors that could previously only be operated manually can be easily automated using an adaptive model predictive control technology. The barrier to automation of the reactor batch controls can be now removed resulting in tremendous improvements in batch consistency, batch cycle times, and productivity.

Key words: Adaptive Control, Model Based Predictive Control ($MBPC$), Laguerre Identification, Control of batch reactors, Temperature Control, DowTherm

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1 Introduction

Control of processes involving the heating and cooling of a closed batch reactor are a real problem for conventional Proportional-Integral-Derivative (PID) based loop controllers, due to the reduced stability margins typical for these applications. These processes exhibit long dead times and time constants and have an integrating response due to the circulation of the heating or cooling medium through coils within the reactor or jackets on the outside of it.

The advanced controller described in this paper has the ability to model and control marginally stable processes with long and time varying delays. This controller exhibits the ability to incorporate and model the effect of known and unknown disturbances. The field application results presented are demonstrating that reactors which could previously only be operated manually can now automated using model predictive control technology. The barrier to automation of the reactor batch controls is removed resulting in improvements in batch consistency, batch cycle times and productivity.

A number of industrial applications of advanced control methods are reported for batch processes. The limitations of these schemes are fundamentally connected with the application. These schemes lack the generality required to solve batch reactor industrial control in an unified manner. Schemes previously proposed for this application include conventional feedback control with feed forward compensation [3], gain scheduling or multiple models [4,5], generic internal model control [6] and adaptive regulators [7,8]. The typical batch process variables evolve over a wide range therefore time linear invariant models tend to fail in describing completely the process dynamics. Few authors are looking into these challenges from the perspective of predictive control [9–12]. Some authors [13,14] are reporting applied adaptive control techniques. However, a potential problem of their approach can arise from the identification scheme adopted (e.g. the use of ARMAX models limits the generality of the approach). Also, in the case of grey box models used, as in [13], an intimate knowledge of the plant is required.

The paper content is split in six sections. After the introduction containing achievements to date in the second section the theory behind dynamic modelling and control is addressed. The third section describes the process to be controlled. In the fourth section the results concerning the controlled process are provided. Other successful applications are encompassed in section five followed by conclusions in section six.

2 The adaptive predictive control strategy

Based on an original theoretical development by Dumont et al. [26,21] the controller was first developed for self regulating systems. This controller was credited by various users with features like reduced effort required to obtain accurate process models, inclusion of adaptive feed forward compensation and ability to cope with severe changes in the process etc.

These features together with a recognized need in process control industry made the authors of this paper consider a further development of the control strategy for a controller capable of dealing with integrating systems with delay in the presence of unknown output disturbances. The result of these investigations was an indirect adaptive controller based on on-line identification using an orthonormal series representation together with a model based predictive controller.

2.1 Laguerre modelling for integrating time delay systems

Several indirect adaptive control schemes using black box models have been applied on a batch reactor by a number of researchers. No information about the detailed chemical or physical process occurring in the system has been considered. This approach in process control was justified by the difficulty associated with obtaining an analytical model. The common solution employed ARMA models. This solution is associated with a number of problems at the level of the estimation accuracy. Also, if the ARMA model has a smaller order than the plant, the estimation of its parameters depends on the input dynamics, hence in some cases the resulting model can be unstable. ARMA modelling proved to be sensitive to plant model input and output scaling.

The discrete time Laguerre functions identification is avoiding most of the above shortcomings. Continuous Laguerre functions have a history of engineering applications of almost fifty years [19,20]. The motivation of using them as a basis is generated by the simple Laplace representation. Also, we should emphasize their orthogonality as a main advantage. Special care is applied when digitizing the continuous Laguerre model, as in [21].

Choosing a modified sample and hold that suits our purpose:

$$G_{hold}(s) = \frac{e^{sT} - 2 + e^{-sT}}{Ts^2} \tag{1}$$

where $G_{hold}(s)$ approximates a continuous function signal by a line between two sampling points for a given sampling time T.

The result of using this hold in the discrete state space is: $l(k+1) = Al(k) + Bu(k)$ where A and B are part of the Laguerre Network and are described by:

$$A = \begin{bmatrix} \tau_1 & 0 & \cdots & 0 \\ \frac{-\tau_1\tau_2-\tau_3}{T} & \tau_1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ \frac{(-1)^{N-1}\tau_2^{N-2}(\tau_1\tau_2+\tau_3)}{T^{N-1}} & \cdots & \frac{-\tau_1\tau_2-\tau_3}{T} & \tau_1 \end{bmatrix} \tag{2}$$

$$B^T = \begin{bmatrix} \tau_4 & (-\tau_2 T)\tau_4 & \cdots & (-\tau_2 T)^{N-1}\tau_4 \end{bmatrix} \tag{3}$$

where

$$\tau_1 = e^{-pT} \tag{4}$$

$$\tau_2 = T + \frac{2}{p}(e^{-pT} - 1) \tag{5}$$

$$\tau_3 = -Te^{-pT} - \frac{2}{p}(e^{-pT} - 1) \tag{6}$$

$$\tau_4 = \sqrt{2p}\frac{(1-\tau_1)}{p} \tag{7}$$

The system output $y(k) = Cl(k)$ can be obtained as a weighted sum of the Laguerre filters outputs, see Fig. 1. As a result a simple recursive least squares (RLS) identification can be used to solve the optimization problem of choosing the best fit of the Laguerre network to match the process dynamic response.

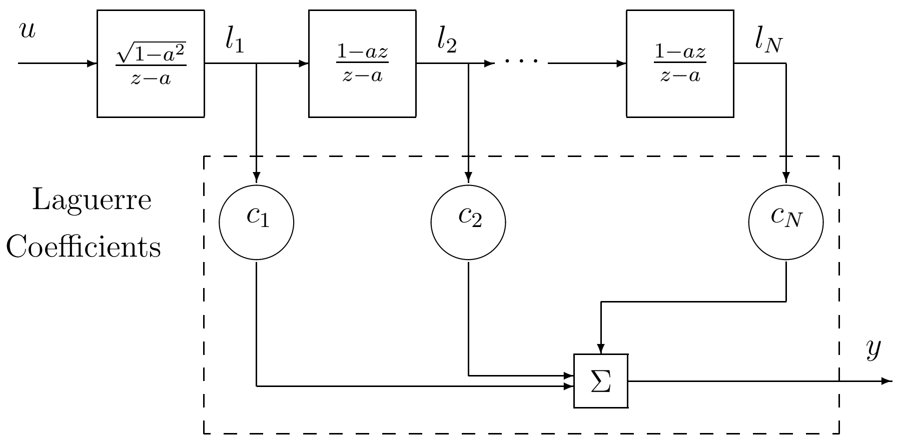

Fig. 1. The Discrete Time Laguerre Network of a Self-Regulating System

An essential issue is that this state space, reflecting the self regulating dynamic system response, is stable, observable and controllable for a given pole a. This is a significant advantage if such a model is to be obtained on-line also in the case of a stability proof. The natural downside of this approach is that we can estimate only self-regulating systems. A further derivation of this algorithm is needed to cope with linear time invariant integrating systems.

The pole of the continuous Laguerre function transfers into a pole of the discrete time system located at a, usually called the time scale of the system. An exact z-domain transfer function representation can be given for the state space above defined:

$$L_i(z) = \frac{\sqrt{(1-a^2)}}{z-a}\left(\frac{1-az}{z-a}\right)^{i-1} \tag{8}$$

The plant model accuracy at crossover frequency is very important from the perspective of the closed loop system transient response. A a good choice for the Laguerre pole will be in that frequency region. Further the choice of the discrete Laguerre function pole can be restricted to a fixed value providing a good choice for the system sampling rate T. Choosing an appropriate sampling time the time scale of the system will be changed. This is part of the solution adopted in the case of the real time implementation when for reasons like speed of the computation, a fixed choice for the pole is required.

The next step in building the Laguerre network relies on the fact that any causal and asymptotically stable sampled linear system $G(z)$ can be expressed as:

$$G(z) = \sum_{i=1}^{\infty} c_i L_i(z) \tag{9}$$

The Laguerre based identification algorithm proposed employs a number of free parameters upon which the designer has control. For practical reasons the discrete Laguerre plant model has to use a finite number of filters. In our implementation the maximum number is $N = 15$, therefore $G(z)$ will be approximated by $\hat{G}(z)$ defined as:

$$\hat{G}(z) = \sum_{i=1}^{N} c_i L_i(z) \tag{10}$$

Hence, note that a Laguerre model can be always transformed into a transfer function but a general transfer function can only be approximated by a finite Laguerre orthonormal basis. In a similar fashion, as in the case of a Pade approximation, the dead time of the process is well modelled by a Laguerre network, depending on its number of filters. A tradeoff has been observed, when modelling a system, between dead-time modelling accuracy and the model settling time. Too many filters will result in a long process model settling time.

A real time implementation being sought, a database with the state space representations for several choices of dead-time and time constant but fixed pole in the case of simple first order systems, was build and stored. This data base is used during reset and startup procedures of the commercial controller and reflects best this compromise.

In the case of an integrating system we have knowledge of the existence of the integrator both in the plant and/or the disturbance model. In order to use a discrete time Laguerre network suitable for self regulating systems our option is to account just for the evolution of the stable part of the plant. Hence, the integrating characteristic removed through a differentiator.

To produce an initial model for control, used also in the identification process as a starting point, the steady state behavior is requested for the process variable. In the case of an integrating system steady state is achieved only when the contribution of the plant and the disturbance into the process variable (PV) are matching. For this reason a method to remove the integrating characteristic of the response has been developed. To estimate if the plant is at equilibrium a batch least squares is used to determine the integrating process slope. If this slope is smaller than the threshold the plant is therefore assumed at equilibrium and learning started.

2.2 Real time predictive control method

It is known that the concept of predictive control involves the repeated optimization of a performance objective (11) over a finite horizon extending from a future time (N_1) up to a prediction horizon (N_2) [23,24].

Figure 2 characterizes the way prediction is used within the $MBPC$ control strategy. Given a set-point $s(k+l)$, a reference $r(k+l)$ is produced by prefiltering and is used within the MBPC cost function (11):

$$J(k) = \sum_{l=N_1}^{N_2} \|(\hat{y}(k+l) - r(k+l)\|^2_{Q(l)} + \sum_{l=0}^{N_u-1} \|\Delta u(k+l)\|^2_{R(l)} \qquad (11)$$

Manipulating the control variable $u(k+l)$, over the control horizon (N_u), the algorithm, as a result of an optimization drives the predicted output $\hat{y}(k+l)$, over the prediction horizon, towards the reference.

In normal operation the weights $Q(l)$ and $R(l)$ are independent of k. The norm

$\|.\|_Q^2$ within the cost function is defined as $\|x\|_Q^2 = x^T Q x$. For prediction it is assumed that $\Delta u(k+l) = 0$ for $l \geq N_u$. The prediction model is based on the current representation of the plant model. As formulated, the optimization is a quadratic programming (QP) problem, and can be solved using standard algorithms. In the absence of constraints the problem resumes to a simple least squares (LS) problem.

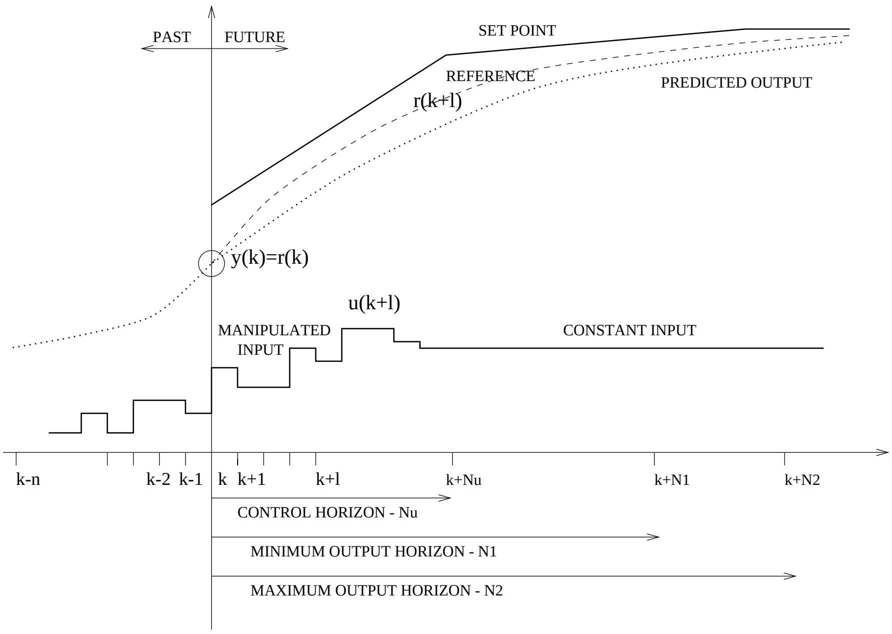

Fig. 2. The *MBPC* prediction strategy

In the case of the advanced controller implementation, a simplified version of the *MBPC* algorithm designed to ensure a real time implementation of the whole indirect adaptive scheme, based on a sampling time as low as 0.1 s for 32 loops simultaneously has been used. Input constraints are managed through a local anti-windup scheme. It is considered [25] that anti-windup has almost similar performance with constrained MBPC for a wide range of plants and control objectives.

The main argument favoring the use of predictive control instead of a conventional passive state or output feedback control technique is its simplicity in handling plant model changes.

The simplified version, a certainty principle based controller, is characterized by the fact that the N_2 steps ahead output prediction $(y(k+N_2)$ is assumed to have reached the reference trajectory value $r(k+N_2)$. As shown in Fig. 2 a first order reference trajectory filter can be employed to define the N_2 steps ahead set-point for the predictive controller $(r(k+N_2))$:

$$r(k+N_2) = \alpha^{N_2} y(k) + (1 - \alpha^{N_2}) s(k)$$

In other words we can write:

$$r(k+N_2) = \hat{y}(k+N_2) = y(k+N_2) + y_d(k+N_2) + y_f(k+N_2) \qquad (12)$$

where d and f are corresponding to the effect of unmeasured and measured disturbance, respectively. Making an essential assumption that the future command stays unchanged: $u(k) = u(k+1) = \cdots = u(k+N_2)$ then the N_2 steps ahead predictor becomes:

$$\begin{aligned} y(k+N_2) = & \, y(k-1) + \delta(k)l(k) + \delta_d(k)l_d(k) + \delta_f(k)l_f(k) + \beta_d(k)\hat{u}_d(k) + \\ & \beta_f(k)u_f(k) + \beta(k)u(k) \end{aligned} \qquad (13)$$

where $\delta(k$, $\delta_d(k)$, $\delta_f(k)$, $\beta(k)$, $\beta_d(k)$ and $\beta_f(k)$ are dependent on the state and observation matrix of the plant, known and unknown disturbance models, respectively. Note that here $u(k)$ is unknown, $u_d(k)$ (the estimated disturbance model input) is estimated and $u_f(k)$ (the measured disturbance model input) is measured.

It is obvious from the above definitions that if a designer is not looking beyond the dead time of the system β_* is zero. One must choose N_2 such that β is of the same sign as the process static gain and of sufficiently large amplitude. A possible criterion to be satisfied when choosing the horizon N_2 is:

$$\beta(k) sign(C(k)(I-A)^{-1}B) \geq \epsilon |C(k)(I-A)^{-1}B| \qquad (14)$$

with $\epsilon = 0.5$. Note that in the simple case of a minimum variance controller the matrix $(I-A)^{-1}B$ can be computed off-line as it depends only on the Laguerre filters. Additional computation has to be carried on-line since the models (i.e their Laguerre coefficients: $C(k)$, $C_f(k)$ and $C_d(k)$) are changing.

Solving the control equation (12) for the required control input $u(k)$ we have:

$$\begin{aligned} u(k) = & \, \beta(k)^{-1}(y_r(k+N_2) - (y(k-1) + \delta(k)l(k) + y_d(k-1)\delta_d(k)l_d(k) + \\ & + y_f(k-1) + \delta_f(k)l_f(k) + \beta_d(k)\hat{u}_d(k) + \beta_f(k)u_f(k))) \end{aligned}$$

To track ramp references, in the spirit of internal model control, the plant model needs to be augmented with an integrator. Such references are quite common in the case of batch reactors. The integrator is used directly in the controller output:

$$\begin{aligned} u(k) &= u(k) + i(k) \\ i(k) &= i(k-1) + \gamma k_i(r(k) - y(k)) \end{aligned}$$

where γ has a nonlinear characteristic to carefully account for a number of updates when the augmented integrator is active following a set-point change. This strategy has been employed since this controller is to be applied to a wide variety of processes among which only a few have ramping set-points. For step set-points and to improve the controller's stability margins this integrator term is not directly required.

Further the plant, disturbance and feedforward states are updated allowing the computation of the output estimations $\hat{y}(k)$, $\hat{y}_f(k)$ and $\hat{y}_d(k)$. The input to the unknown disturbance model is estimated as:

$$\hat{u}_d(k+1) = \hat{y}(k) + \hat{y}_f(k) + \hat{y}_d(k) - y(k) \tag{15}$$

2.3 The indirect adaptive predictive control solution

When compared with classic or robust control techniques, adaptive control has a number of features. Such algorithms provide: i)on-line corrections of the model function of the changes in the plant dynamics, reducing the system sensitivity; ii) simple structure and design; iii)an attractive solution for automatic tuning of process control loops; iv)control performance for systems with unknown parameters

In model based control the plant model has to be identified in order to produce a control action. Using the discrete time Laguerre model we observe that the weights c_i of each individual Laguerre orthonormal term arranged in the matrix C, for a given pole and number of filters, can be selected to approximate the plant or disturbance model. A modified recursive least square (RLS) algorithm to estimate these parameters is employed. The RLS procedure is used at each time step to obtain the parameter vector together with the covariance matrices. This procedure is minimizing the memory usage since no matrix inverse, old input, output or Laguerre coefficients data is stored. The properties of the least squares algorithm (i.e. the non-biased estimation when no model structure error and white measurement noise) are readily transferred to the recursive algorithm, see [27]. In the case of no correlation between the output measurement noise and the input sequence the bias is guaranteed zero. Enough excitation (e.g. through set-point changes) can ensure fulfillment of this condition. In [28] a condition for a signal to be sufficiently rich is stated.

When we approximate a nonlinear system by a linear model and when the operating condition changes the approximated model parameters also change. To correctly estimate the model parameters the assumption that their rate of change is slower than the sampling time is required. The forgetting factor (i.e. an exponentially decaying weight) is added to the measured data sets (e.g. heavy weighting is assigned to the most recent data due to its importance, versus a small weight in the case of older data).

The core of the recursive least squares algorithm is the update of the covariance matrix:

$$P(k+1) = \frac{1}{\lambda}\left[P(k) - \frac{P(k)l(k+1)l(k+1)^T P(k)}{\lambda + l(k+1)^T P(k) l(k+1)}\right] + \mu I + \nu P(k)^2 \quad (16)$$

This update includes the additional terms weighted by μ and ν for improved stability of the estimation, see [29], and is repeated in a similar manner for $P_f(k+1)$ and $P_d(k+1)$. Through the introduction of the two additional terms μI and $\nu P(k)^2$ covariance matrix resetting and boundeness is achieved, respectively, see [29].

Finally the model estimate is obtained by adding a correction to the previous estimate. The correction is proportional to the difference between the real output of the plant or disturbance and its prediction based on the previous parameter estimate:

$$C(k+1) = C(k) + \frac{\alpha P(k) l(k+1)}{\lambda + l(k+1)^T P(k) l(k+1)} e(k) \quad (17)$$

This procedure is repeated in a similar manner for the matrices of Laguerre coefficients: $C_f(k+1)$ and $C_d(k+1)$. Typical values for these parameters used inside the controller are $\alpha = 0.1$, $\lambda \in [0.9, 0.99]$, $\mu = 0.001$ and $\nu = 0.001$. Note that for a constant input the state update will reproduce the previous state and therefore the Laguerre coefficients will be unchanged. This mechanism avoids convergence to wrong values when there is no process persistent excitation. The algorithm is expected to converge if the model error is small and the input signal "rich" enough.

For better performance we had to extend further the on-line identification scheme and account for unmeasured disturbances. It is recognized that disturbances can i)affect the system output; ii)be involved as loads at the plant input; iii)added in the middle of a process. In the former two cases the measured effect is obtained filtered through a transfer function that includes completely or partially the model. Based on the definition of the disturbance and the plant model we can always locate the disturbance effect at the plant output.

The practical issue raised by this approach is: "How can we estimate the sequence used as an input to the unknown disturbance model?". Our approach assumes that the unknown $\hat{u}_d(k)$ is estimated as in equation (15) In practice the steps leading to the computation of $u_d(k)$ are iterated a number of times at reset for fast convergence.

The complete learning procedure involves an update for the plant and known and unknown disturbance models state estimates based on their corresponding models. Knowing the model states, the plant and known and unknown disturbance models outputs are updated. Often the unknown disturbance model is fixed to predefined values reflecting the type of disturbance possible to encounter.

In performing the on-line model identification the controller checks if: i) the modelling flag is enabled, ii) the process variable (PV) $y(k)$ is within the learning range and iii) a set point (SP) $s(k)$ change in "auto" mode or a control variable (CV) $u(k)$ change in "manual" mode exceeding predefined thresholds has occurred.

Industrial reality has generated the requirement for the indirect adaptive predictive controller to have the capability of switching the models used for control. The control law is computed at each time instant hence for the most general case issues of stability and the convergence of the method become paramount. In [1] these issues are partially addressed. The multi-model scheme is using a hysteresis type switching to avoid instability.

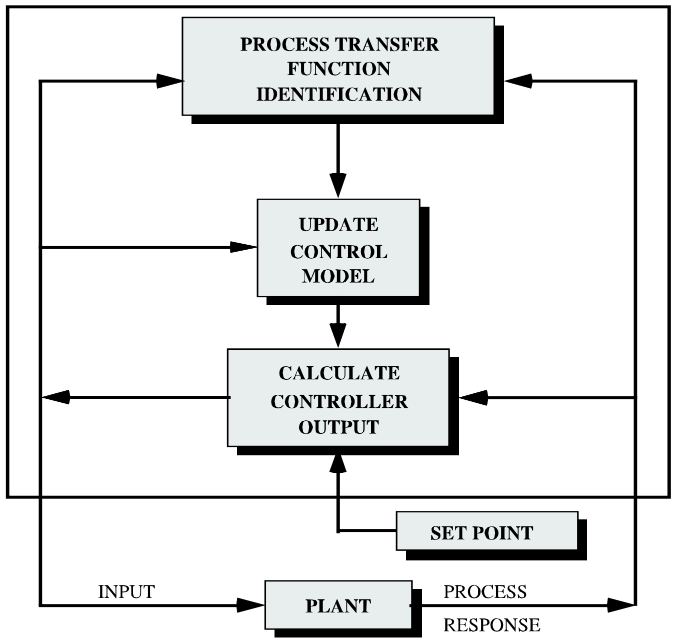

Fig. 3. The closed loop of the advanced control system applied to the batch reactor

The closed loop system depicted in Figure 3 is implemented in C++ and runs on the Windows^{TM} 2000 operating system. An OLE for process control (called OPC server) is used to communicate to the existent Distributed Control System (DCS). Logic was programmed in the DCS device to allow operation from the existing operator console. The operator can select between manual, PID (DCS) or advanced control modes.

3 A batch reactor processes

The chemical batch reactor in this application is used to produce various polyester compounds. The process involves combining the reagents and then applying heat to the mixture in order to control the reactions and resulting products. A specific temperature profile sequence for the batch reaction must be followed to ensure that the exothermic reactions occur in a controlled fashion and that the resulting products will have consistent properties. An additional requirement is that the reaction rates must be controlled to limit the production of waste gases that must be incinerated to the design capacity of the incinerator. The potential of an uncontrolled exothermic reaction is present in some batches and proper temperature control is critical to regulating these reactions and preventing explosions.

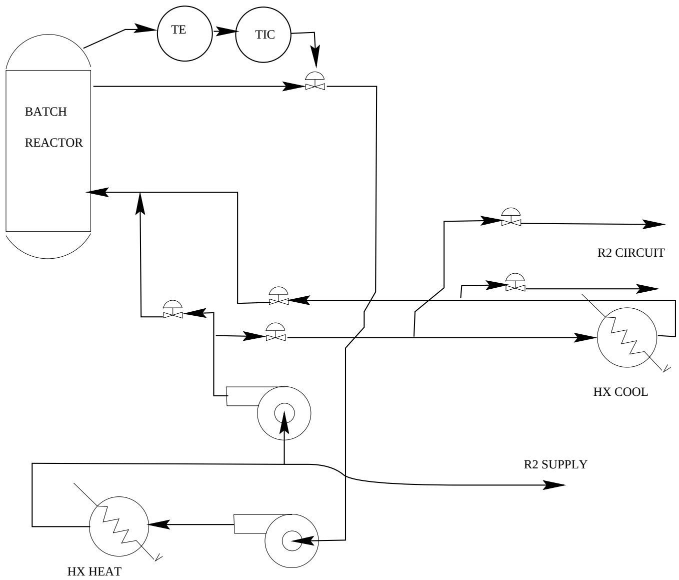

Fig. 4. The simplified scheme of a batch reactor system

The reactor operates in a temperature range between 70 and 220 F° and is heated by circulating a fluid (DowTherm-G) through coils on the outside of the reactor. This fluid is in turn heated by a natural gas burner to a temperature in the range of 500 F°. The reactor temperature control loop monitors temperature inside the reactor and manipulates the flow of the DowTherm fluid to the reactor jacket. Increasing the flow increases heat transfer rate to the reactor. It is also possible to cool the reactor by closing the valves on the heat circuit and by re-circulating the DowTherm fluid through a second heat exchanger. Cooling is normally only done when the batch is complete to facilitate product handling. Refer to Figure 4 for a simplified schematic of the system. The temperature response of the reactor and the temperature response of the DowTherm fluid at the outlet of the reactor jacket coils are shown in Figure 5.

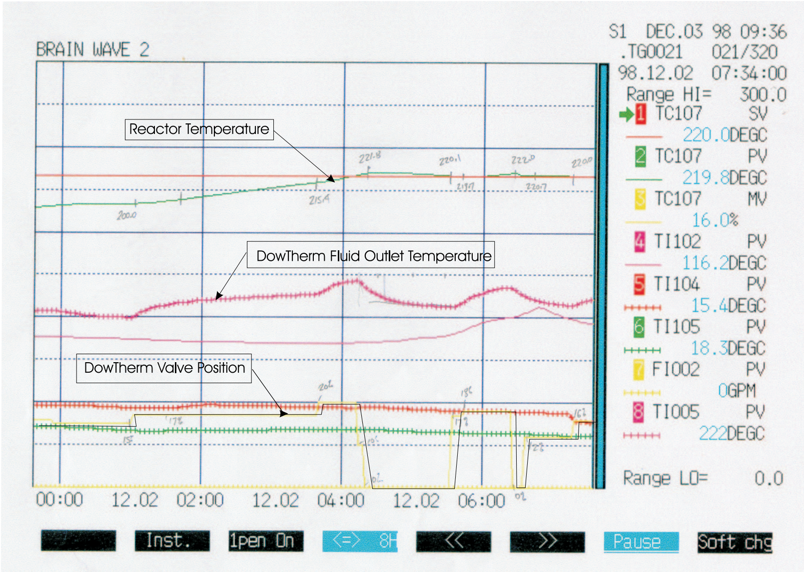

Fig. 5. The batch reactor system response under manual control

The process engineers at the plant made several unsuccessful attempts to automate control of the reactor temperature using a conventional PID controller. The reactor temperature is difficult to control because of the long dead time (about 8 minutes) and long time constant (about 18 minutes) associated with heating the reactor from the outside. This is further complicated because the system essentially behaves as an integrator due to the accumulation of heat in the reactor and is therefore only marginally stable in open loop. PID controllers are not well suited for systems with such response characteristics and can be very difficult to tune for closed loop stability. The reactor was controlled manually by experienced operators and requires constant attention to ensure that a correct temperature profile and resulting reaction rates are correct.

The reactor temperature is stable only if the heat input to the reactor equals the heat losses. If the DowTherm flow is set even slightly higher than this equilibrium point, the reactor temperature will rise at a constant rate until reactor temperature limits are exceeded. The equilibrium point changes during the batch due to heat produced by the exothermic reactions (less heat input required to maintain reactor temperature) and the production of vapors (more heat input to maintain reactor temperature). During the final phase of the batch, the exothermic reactions are complete and the vapor production gradually falls almost to zero. Very little heat input is required to maintain reactor temperature during this phase.

For a better understanding of the plant dynamics the control strategy developed by the operators is revealed. From experience, the DowTherm flow is initially set to a nominal value (17% to 19%) that will cause a slow rise in the reactor temperature. The rate of rise is not constant due to the changes in heat requirements that occur during the batch. If the rate of rise is too fast as to cause an overload of the vapor incinerator or so slow as to stall the temperature rise required to follow the batch profile then the operator will intervene and adjust the flow up or down by 2% to 4%. Otherwise the temperature ramp rate that results from the set DowTherm flow is accepted. During the final phase of the batch, the equilibrium point for the system changes from a DowTherm flow of about 15% to almost 0%. The operators manage this phase by setting the flow to either 20% if the reactor temperature is below set point or 0% if the reactor temperature is above set point because these settings will guarantee that the reactor temperature will move in the desired direction. This control method results in oscillation of the reactor temperature about the set point and requires constant attention by the operator.

In order to reduce the batch cycle time and improve product consistency, the plant desired to automate the temperature profile control sequence. The inability to obtain automatic closed loop control of the reactor temperature was a barrier to batch sequence automation.

4 Application results

The advanced model based controller was implemented on the reactor temperature control loop. The controller parameters were estimated from the observed system response from a previous batch and an approximate model of the system was developed in the controller using 15 Laguerre filters. There was some concern that a single model of the system may not be valid for the entire batch sequence because the composition and viscosity of the polyester in the reactor changes substantially during the batch. The first attempt was based on a single model of the reactor response and the control performance was found to be very good. The controller was left in place and has since been controlling the reactor temperature in automatic.

The integrating type response of the reactor is apparent from the control actions made by the controller as the reactor temperature follows the set point to higher temperature operating points with a final control output at 0%. Note that the batch sequence was suspended and the controller was placed in manual mode for a short time due to a water supply problem at the plant. The batch sequence was later resumed and the controller was placed in automatic for the rest of the batch.

A chart of the temperature control performance of the advanced controller during an entire batch is shown in Figure 6.

The operators now adjust temperature profile set point instead of the DowTherm flow. Complete automation of the batch sequence including automatic set point ramp generation for the reactor temperature is now possible.

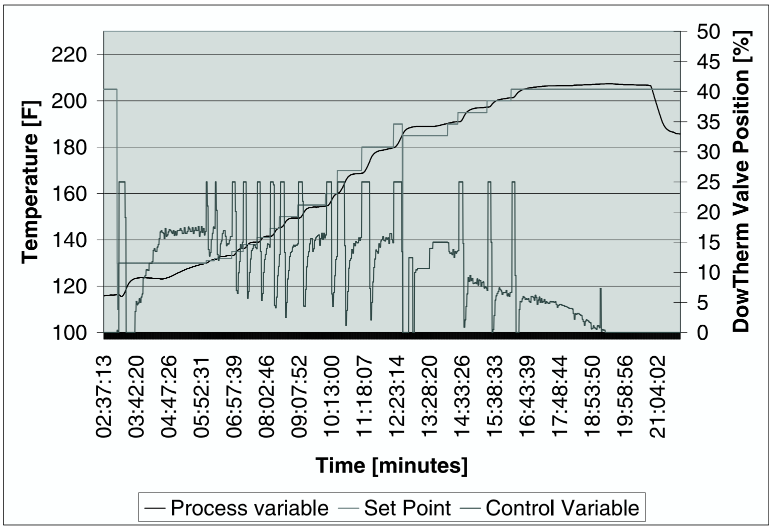

Fig. 6. The batch reactor system response under automatic control

Operation of the reactor is further improved because the rate of vapor production is significantly more constant due to the improved control of the reactor temperature. This helps to avoid overloading of the vapor incinerator and possible violation of environmental emission regulations due to incomplete combustion of the process waste gases.

5 Other successful applications

The model based predictive controller has been implemented on many other industrial processes involving significant time delays. Control of pulp bleaching to achieve a desired brightness following a 40 minute reaction time in a retention tower is among them. In this example, the mill had designed a Smith Predictor compensated PID controller and the model predictive controller was installed to compare performance. The results of this application demonstrated a 48% reduction in pulp brightness standard deviation when using the adaptive model based controller.

Another successful example is the control of excess oxygen to the Claus sulfur recovery process. This process is commonly used by oil and gas refineries to recover sulphur which is a by-product of the refining process. Control of oxygen is critical to maximize recovery and reduce sulfur emissions as it effects the stoichiometries of the reaction. Oxygen is adjusted to maintain the concentration of the hydrogen sulfide and the sulfur dioxide at a ratio of 2:1 at the last stage of the Claus reactor. In this example the refinery used a PID controller with a feed forward calculation for air demand based on flow of the process stream. The adaptive model based predictive controller was also configured to model the process stream flow as a feed forward variable. The process time delay was about 90 seconds with a time constant of about 60 seconds. The advanced controller achieved a 38% reduction in standard deviation of the hydrogen sulfide to sulfur dioxide ratio compared to the PID control scheme. The improved control resulted in a 0.2 to 0.3 % increase in sulfur recovery.

6 Conclusions

An advanced model based predictive controller $MBPC$ developed for use on processes with an integrating response exhibiting long dead time and time constants has been successfully applied to the temperature control of a batch reactor. The controller was easy to apply and configure. It has achieved very good control performance on a reactor that could not be controller in a satisfactory manner using PID controls implemented in the plant DCS.

The automatic control of the reactor temperature now enables the plant to reduce batch cycle time, to increase plant productivity and to improve product quality and consistency through an automated batch sequencer.

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