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

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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 based loop controllers. Tuning can be extremely difficult due to the reduced stability margins proved for these types of processes. This paper describes the application of a new advanced process controller that is designed to handle integrating-type processes with long dead times and long time constants. The results described demonstrate that reactors that could previously only be operated manually can be easily automated using model predictive control technology. The barrier to automation of the reactor batch controls can be removed, resulting in the opportunity for tremendous improvements in batch consistency, reduced batch cycle times, and improved productivity.**

Keywords—Adaptive Control, Model Based Predictive Control (MBPC), Laguerre Identification, Control of batch reactors, Temperature Control, DowTherm.

1. Introduction

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, due to the reduced stability margins present in 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 the reactor.

The advanced controller described in the paper has the ability to model and control marginally stable processes with long time delays and long time constants. The controller also incorporates and models the effect of known and unknown disturbances.

The field application results presented in this paper demonstrate that reactors that could previously only be operated manually can be easily automated using model predictive control technology. The barrier to automation of the reactor batch controls can be removed resulting in significant improvements in batch consistency, reduced batch cycle times, and improved productivity.

The second section of this paper addresses the theory behind the dynamic modeling and control. The third section describes the process to be controlled. In the forth section the results show the benefits of this technique when coping with a real world application. Other applications are listed too in the fifth section.

2. The Adaptive Predictive Control Strategy

Based on an original theoretical development by Dumont et al [1, 2], the controller was first developed for self-regulating systems. This controller was credited by various users with several features, among which we can mention: the reduced effort required to obtain accurate process models, the inclusion of adaptive feedforward compensation, the ability to cope with severe changes in the process etc. All these features together with recognized industrial need made us consider further development of the control strategy to deal with integrating systems with delay in the presence of unknown output disturbances. The result of these investigations was an indirect adaptive controller based on the on-line identification using an orthonormal series representation working together with a model based minimum variance predictive controller.

Process Modeling using Laguerre Series Representation

Dumont et al [3] considered system identification based on Laguerre orthonormal functions. This method proved its simplicity when dealing with the representation of transient signals, closely resembling the Pade approximation for systems exhibiting dead time. The Laguerre function, a complete orthonormal set in L_2, has the following Laplace domain representation:

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

where: i is the number of Laguerre filters (i = 1, N), $p > 0$ is the time-scale, $L_i(x)$ are the Laguerre polynomials.

The simplicity of the Laguerre ladder network, is shown in Fig.1.

This network can be expressed as a stable, observable and controllable state space form, with A a lower triangular square (N x N) matrix, as:

$$l(k+1) = Al(k) + bu(k) \tag{2}$$

$$y(k) = c^T l(k) \qquad (3)$$

where: $l(k)^T = \left[l_1(k), \quad \dots \quad , l_N(k) \right]^T$ is the state of the ladder (i.e., the outputs of each block in Fig. 1.), and $C_k^T(k) = \left[c_1(k), \quad \dots \quad , c_N(k) \right]$ are the Laguerre coefficients at time k.

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

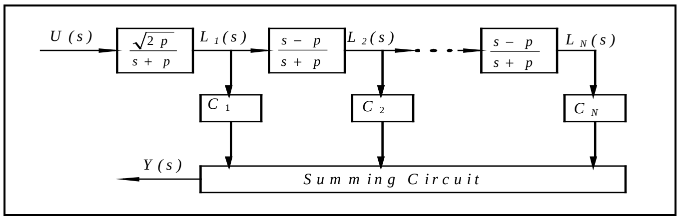

Fig. 1. The Laguerre Ladder Network

The above form is suitable to represent stable systems. The challenge is to overcome the integrating characteristic of the plant model. In these circumstances, the approach taken is a factorization of the plant into its stable and marginally stable parts, the latter considered known. Note that the same procedure can be applied to a plant that contains well-known unstable dynamics as well. Of course the robustness of the identification method applied to the global plant is conditioned by the exact knowledge of the marginally stable or unstable part of it.

This approach will lead in discrete time to a SISO controller that uses variations of the process variable (system output) $\Delta y(k)$ to provide control variable movements (system input) $u(k)$.

The same concept used in the plant identification is used to identify the process load (output disturbance). In this case the major difference is that the controller does not have access to the disturbance model input. This issue is addressed in a stochastic manner that provides an estimate of the load. The development is based on the observation that an external white noise feeds the disturbance model, resulting in a colored signal. This signal 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 develop the Model Based Predictive Control (MBPC) strategy.

The Predictive Control Strategy

The 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) [4, 5]. 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 MBPC 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.

In this paper we deal with a simplified version of the MBPC algorithm because we have to ensure real time implementation of the whole indirect adaptive scheme, based on a sampling time of 1s.

Predictive control is used instead of a conventional passive state or output feedback control technique due to is its simplicity. In handling varying time delays and non-minimum phase systems.

The simplified version, i.e., minimum variance control, 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 $y_r(k + N_2)$. In other words we can write:

$$\begin{aligned} y_r(k + N_2) = y(k + N_2) &= y(k) + y_d(k + N_1) \\ &+ y_{ff}(k + N_2) + C_k^T (l(k + N_2) \\ &- l(k)) \end{aligned} \qquad (4)$$

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:

$$\begin{aligned} y(k + N_2) = y(k) &+ k^T l(k) + k_d^T l_d(k) + \\ &k_{ff} l_{ff}(k) + \beta_d u_d(k) + \beta_{ff} u_{ff}(k) + \\ &\beta u(k) \end{aligned} \qquad (5)$$

where:

$$\begin{aligned} k^T &= C_k (A^{N_2} - I) \\ k_d^T &= C_d (A_d^{N_2} - I) \\ k_{ff}^T &= C_{ff} (A_{ff}^{N_2} - I) \\ \beta &= C_k^T (A^{N_2} + \cdots + I) b \\ \beta_d &= C_d^T (A_d^{N_2} + \cdots + I) b_d \\ \beta_{ff} &= C_{ff}^T (A_{ff}^{N_2} + \cdots + I) b_{ff} \end{aligned}$$

Note that here $u(k)$ is unknown, $u_d(k)$ (the estimated disturbance model input) is estimated and $u_{ff}(k)$ (measured disturbance model input) is measured. β_* is the sum of the first N_2 parameters of each corresponding system (i.e. plant, stochastic disturbance and deterministic disturbance, respectively).

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:

$$\beta \operatorname{sign}(C_k^T (I - A)^{-1} \underline{b}) \geq \varepsilon \left| C_K^T (I - A)^{-1} b \right| \qquad (6)$$

with $\varepsilon = 0.5$. 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 out on-line since the identified models (i.e., their Laguerre coefficients: C_k, C_{ff}, and C_d) are changing.

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 ($y_r(k + N_2)$):

$$y_r(k+N_2) = \propto^{N_2} y(k) + (1-\propto^{N_2} y_{sp}) \qquad (7)$$

Solving control equation (4)) for the required control input $u(k)$ we have:

$$u(k) = \beta^{-1}(y_r(k+N_2) - (y(k) + k^T l(k) + k_d^T l_d(k) + k_{ff} l_{ff}(k) + \beta_d u_d(k) + \beta_{ff} u_{ff}(k))) \qquad (8)$$

Indirect Adaptive Control Scheme

As briefly mentioned in the introduction, the indirect adaptive control scheme suggested uses a modified recursive least square algorithm [6] to estimate the parameters of the models involved in control equation (4). Since the control law is computed at each time instant, issues of stability and the convergence of the method become paramount. In [1] these issues are partially addressed.

The adaptive control identification algorithm has a number of free parameters. A designer has to minimize this number since the scheme is implemented in real time. For instance the choice of the Laguerre filter pole p can be restricted to a fixed value providing a good choice for the system sampling rate. For a given plant there is an optimal pole that will minimize the number of filters required to obtain a required accuracy for the model.

In a similar fashion, as in the case of a Pade approximation, the dead time of the process is well modeled by a Laguerre network, depending on its number of filters. A tradeoff has been observed between the dead-time modeling and the model settling time. Too many filters will result in a long process model settling time.

Since the model of the plant at crossover frequency is very important from the perspective of the transient response of the closed loop system, a good choice for the Laguerre pole will be in that area. If, for other reasons, a fixed choice for the pole is required, then choosing an appropriate sampling time can change the time scale of the system.

We have knowledge of the existence of the integrator both in the plant and in the disturbance models, therefore our option was to predict the evolution only of the stable part of the plant and load models and then add the integrator directly in the control law. This path is motivated by the choice of the cost function used in computing the optimal control movement (*u(k))*. Another version, under development, includes a full MBPC cost function. This approach, as described [8], augments the plant model (including the known marginally stable or unstable part) with the disturbance model and computes the control movement based on the prediction of the augmented model.

The closed loop system is depicted in Fig. 3. The advanced controller [7] was implemented in C++ and runs on the Windows-NT™ operating system. An OLE for process control (called OPC server) is used to communicate to the 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.

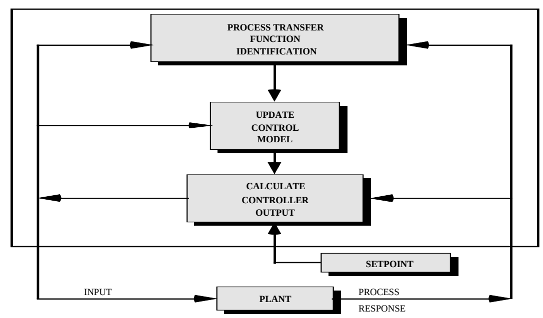

Fig. 3. The Closed Loop Advanced Control System

3. 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 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.

The reactor operates in a temperature range between 70 and 220°C 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°C. 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.

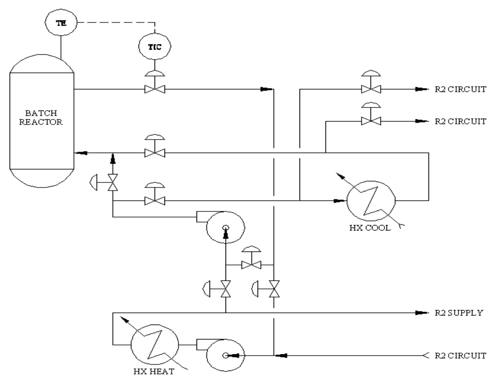

Fig. 4. The Simplified Scheme of a Batch Reactor System

Refer to Fig. 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 Fig. 5.

The plant has made several unsuccessful attempts to automate control of the reactor temperature using a conventional Proportional-Integral-Derivative (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 these response characteristics and can be very difficult to tune for closed loop stability. The reactor can only be controlled manually by experienced operators and requires constant attention to ensure that the temperature profile and resulting reaction rates are correct. This control method results in oscillation of the reactor temperature about the set point and requires constant attention by the operator.

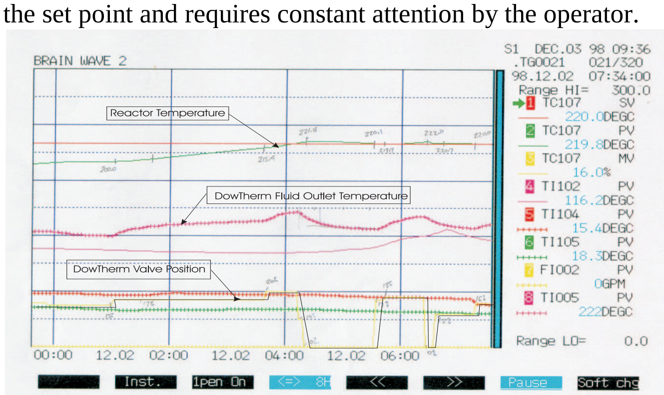

Fig. 5. The Batch Reactor System Response (Manual Control)

For all the above information Fig. 5. is relevant. It should be noted that a second reactor at this plant was successfully automated using PID control, but this reactor is heated from internal coils and has a much shorter dead time and time constant and is thus easier to control. 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 vapours (more heat input to maintain reactor temperature). During the final phase of the batch, the exothermic reactions are complete and the vapour production gradually falls almost to zero. Very little heat input is required to maintain reactor temperature during this phase.

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 an open loop system identification based on Laguerre series representation. 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.

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

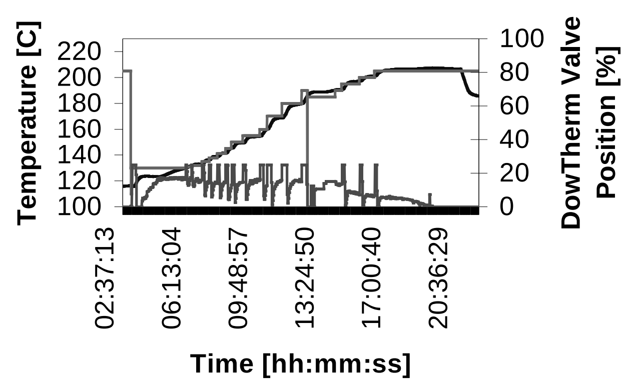

Fig. 6. Automatic control of the Batch Reactor System

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.

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.

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

5. Other Succesfull 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 a difficult problem due to the long time delay between addition of the bleaching chemical and the measurement of the final pulp brightness. 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 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 stoichiometrics 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 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 model based predictive 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.

These examples illustrate the practical problems that industry experiences with the control of processes that exhibit time delay using conventional PID controllers. The model based predictive controller described in this paper provides a practical alternative to PID control to enable industry to better deal with the common problem of time delay in process control.

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 controlled satisfactorily 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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