Adaptive Control of Integrating Time Delay Systems: A PVC Batch Reactor

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Abstract— **Batch processes are a real challenge for conventional Proportional-Integral-Derivative (PID) controllers. PID tuning can be extremely difficult due to the reduced stability margins. An industrial indirect adaptive control scheme was developed and applied to more than two dozen processes with an integrating time delay characteristic. Among these a Polyvinyl Chloride (PVC) batch reactor was chosen to illustrate the performance of the proposed method. The scheme, which uses identification based on Laguerre functions and predictive control, allows easy automation of batch reactors. This control strategy resulted in improved batch consistency, reduced cycle times and increased productivity.**

Keywords— **Indirect adaptive predictive control, Laguerre orthonormal functions, PVC batch reactor, Time delay, Integrating systems**

I. Introduction

THe control of Batch Polyvinyl Chloride (PVC) reactors has to operate over a large operational envelope and a variety of recipes. As a result, the controller has to cope with process nonlinearities, varying time delays, integrating characteristics and saturation constraints.

PID control for batch reactors was recently [1] revisited in light of the work by Astrom et al. [2] on Smith predictors modified to cope with integrating processes with long time delay. However, increased robustness resulted in degraded performance. Using a robust controller for the whole operational envelope is simply too restrictive.

Few applications of advanced control of PVC batch reactors have been reported. The schemes adopted include conventional feedback control with feedforward compensation [3], gain scheduling or multiple models [4], [5], generic internal model control [6] and adaptive regulators [7], [8]. Self tuning control [9] together with adaptive pole placement [10] of batch reactors have also been presented as potential techniques for their control. Although these schemes have proved suitable for particular applications they lack the generality required to solve different industrial problems in a unified manner. This is one of the main original features of the current approach.

The typical batch process variables evolve over a wide range, therefore linear time invariant models fail to completely describe the process dynamics. Some authors are looking into these challenges from the perspective of predictive control [11], [12], [13].

The few papers [14], [15] that report adaptive control of batch reactors express concerns about the identification scheme. For instance, the use of ARMAX models limits the generality of the approach. These methods do not use any information about the detailed chemical or physical process occurring in the system. Further, in the case of grey box identification [14], an intimate knowledge of the plant is required. Applications of indirect adaptive control schemes have been reported in [16], [17].

The vast majority of the papers addressing the topic of PVC batch reactor control appeared at the beginning of the last decade and were mostly limited to experimental installations. A recent and comprehensive survey [18] lists 48 commercial applications of batch control and management. In spite of this, most industrial batch processes are controlled manually or by some ad-hoc combination of PID and engineering expertise. Those industrial schemes are generally cumbersome and therefore less reliable from perspectives like the continuous operation and performance.

Adaptive control involves three major steps: model selection, parameter estimation and controller design. Quite often a model based on first principles is difficult to obtain. Therefore, in practice, an approach based on an input output model is more appealing. Although linear models are only valid over a reduced range, they are still commonly selected for control. For a batch reactor the nonlinearities are such that a control based on a fixed linear approximation cannot be satisfactory, hence the motivation for an adaptive scheme.

Adaptive control using a linear Laguerre model was first introduced in [19]. Based on this original theoretical development a commercial controller was developed for self-regulating systems. This controller offers users several attractive features, such as: 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.

In this paper we are proposing an approach for the control of time delay integrating systems[1]based on Laguerre orthonormal basis identification and predictive control. The plant model (e.g. PVC batch reactors) can be arranged in a form that is linear in the parameters, allowing the use of a simple recursive least squares identification scheme. Model based predictive control is then employed

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[1]The concept of integrating time delay system has a history in process control. This definition embeds within additional information on plant dynamics i.e it exhibits simultaneously a marginally stable behavior (it contains an integrator) as well as time delay (also called dead time) between inputs and outputs.

to address the control of batch reactors. The field application results presented are representative of the large number of similar applications performed. They demonstrate that PVC batch reactors which could previously only be operated with poor performance manually or using PID controllers, can now be easily automated.

The original contribution of the work summarized through a specific application in this paper is that a number of techniques have been brought to maturity and then assembled together in a successful commercial product for which we can find usefulness in a number of process industries and beyond.

The paper is organized in eight sections. Section II deals with the dynamics of the PVC batch reactor and its challenges. Sections III and IV are devoted to Laguerre modelling for integrating time delay systems. Section V presents a modified generalized predictive control scheme suitable for real time. Section VI addresses implementation aspects. In Section VII we are showing the results from a typical industrial application. This is followed by conclusions in Section VIII.

II. Dynamics of PVC batch reactors a challenging control problem

Batch processes play an essential role in the chemical and food industries (e.g. in the production of pharmaceuticals, biochemicals and a large number of polymers). Usually each batch run is different due to normal or special variations. The polymerization time varies from batch to batch. Normal variations include the common operational type, like ambient temperature, feed quality etc. In contrast special variations are due to unusual causes such as fouling, drift, disturbances or even operational problems. If present and not detected such problems result in the deterioration of the final product quality. Typically batch behavior is characterized by nonlinearities and non steady state operation. In the case of PVC reactors the propagation reaction should take place under moderate pressure and temperature.

PolyVinyl Chloride (PVC) is produced by a suspension polymerization process, originally developed by Pechiney-St. Gobain and now licensed across Europe, Japan and the United States. The particle size is up to $2\mu m$ for emulsion resins and $0.2\mu m$ for latex. After the materials are loaded into the reactor, an initiator is added to start the reaction. Typical PVC reactors, see Figure 1, have a cooling jacket designed to use a cooling water flow. To improve the cooling process some of the reactors have a condenser on top that removes part of the reaction heat through condensation of the vinyl chloride gas. Water and monomer soluble initiators (e.g. potassium persulfate and azodisobutyronitrile initiator, respectively) are used. The initial rate of the reaction is highly dependent upon the temperature and initiator choice. Emulsifiers, protective colloids and water soluble derivatives are used to improve the mechanical stability and reduce artificial agglomeration of particles during polymerization, their selection being essential since they are present as impurities in the final product.

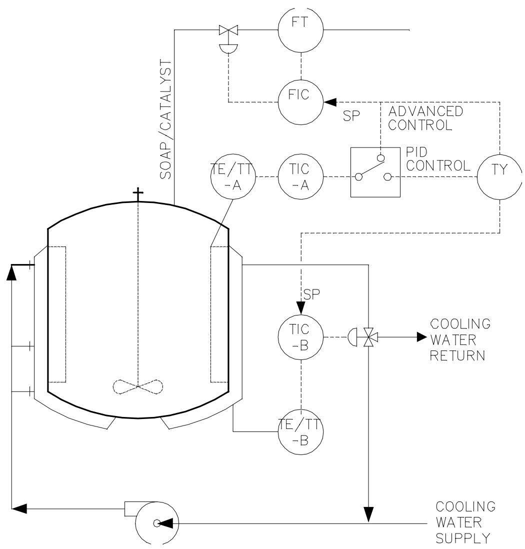

Fig. 1. The schematic representation of a PVC batch reactor including the relevant process (PV) and control (CV) variables under PID and BWC control

Presently used methods involve adding and controlling the "redox" system (e.g. sodium bisulphite), with the aim of improving the effectiveness at low temperatures, at a predetermined time from the beginning of the reaction. This "redox" system is added during the reaction permitting good control over its rate. The conversion process takes place at high mixing rates (e.g 130 rpm) for three hours, during which 10% of the total product quantity is processed. This puts extra emphasis on the temperature profile that a controller is capable of tracking. For the rest of the yield the mixing speed is decreased to 30 rpm for roughly 13 hours. After the reaction is completed, as determined by molecular weight or the amount of monomer conversion, the batch is discharged to a stripper by purging the reactor with nitrogen or other inert gas. The suspension is then centrifuged to a moisture content of 0.2%. Oxygen may also be removed from the water at the beginning of the process. However, since the reaction is highly exothermic, excess heat needs to be withdrawn from the process. For this purpose the presence of water as a continuous phase permits efficient removal of heat. Poor temperature control can cause more rapid buildup of co-polymer on the reactor walls. Cleaning, usually done after ten batches, is a very expensive procedure that reduces the productive time of the reactor. The deposits also affect the cooling capacity of the reactor, hence the time delay and time constant of the system.

In the literature, see [20], there is evidence that isothermal operation is the preferred mode in many batch systems. It has been established that using an isotherm setpoint for series type reaction gives a product which favorably compares to that obtained by imposing an optimal temperature profile. For a single irreversible exothermic reaction, isothermal operation is possibly the best way to ensure safe operation and to prevent runaway. Runaway can result in an uncontrolled release of the monomer in the atmosphere with potentially catastrophic consequences. Note that the product is sold based on average molecular weight, which is directly affected by the temperature of the batch. Hence, tight temperature control is essential both for economic and safety reasons.

III. Laguerre modelling for integrating time delay systems

In black box modelling a common solution is to use Auto-Regressive Moving Average (ARMA) models. However, the use of such models in adaptive control can lead to severe problems. If the ARMA model is underparametrized the estimation of its parameters depends on the input and in some cases the resulting model can be unstable. If on the other hand, the model is overparametrized, loss of controllability can occur. ARMA modelling is also very sensitive to scaling of inputs and outputs.

Over the last 15 years, there has been considerable interest in the use of orthonormal functions in system identification and adaptive control. Interest in the orthonormal series representation of signals goes back to the classical work of Wiener and Lee during the 1930's on network synthesis using Laguerre functions, see [21], [22]. In the 1970's, there was a renewed interest in Laguerre functions, but as a tool for data reduction in system identification. The identification of a closed-loop system in terms of a truncated Laguerre series was considered in [23] for automatic tuning of PID controllers. The use of Laguerre functions in adaptive control was first proposed in [19]. This was followed by a significant increase in activity on the use of Laguerre functions to approximate infinite dimensional systems, e.g. [24], [25]. More recently, approximation of dynamic systems by generalized orthonormal basis functions has been studied by several research groups [26]. The thrust of this recent work has been the development of orthonormal functions specifically tailored to the underlying dynamics of the system to be represented, using balanced realizations. The objective is to capture the essential dynamics of the system in a series expansion involving as few terms as possible.

Several advantages result from the use of an orthonormal series representation of process dynamics, particularly in an adaptive control framework, see [27]. The Laguerre model is an output-error structure, is linear in the parameters and preserves convexity for the identification problem. It eliminates parameter drift due to the influence of unmodelled dynamics on the nominal model, is stable, and robustly stabilizable as long as the unmodelled dynamics are stable. This effectively solves the so-called admissibility problem and makes the Laguerre structure particularly suitable for adaptive control applications in the process industries.

The discrete Laguerre filters are represented by

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

where i is the order of the function ($i = 1,..N$), and $0 < a < 1$ is a free parameter, see [28].

Using the discrete Laguerre functions, a complete orthonormal set in $L_2[0,\infty)$, any causal and asymptotically stable sampled linear system $G(z)$ can be expressed as:

$$G(z) = \sum_{i=1}^{\infty} c_i L_i(z) \quad (2)$$

In practice, the Laguerre model will use a finite number of filters, (in our implementation the maximum number is $N = 15$) i.e. $G(z)$ will be approximated by $\hat{G}(z)$ defined as:

$$\hat{G}(z) = \sum_{i=1}^{N} c_i L_i(z) \quad (3)$$

This can be represented by the simple and convenient ladder network shown in Figure 2.

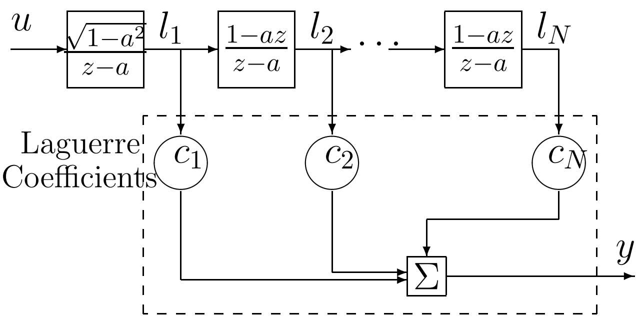

Fig. 2. The Discrete Time Laguerre Network of a Self-Regulating System

This Laguerre ladder network can be expressed in a stable, observable and controllable state-space form as,

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

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

with $l^T(k) = [\ l_1(k) \quad l_2(k) \quad \ldots \quad l_N(k)\ ]^T$, and $c^T = [c_1 \quad c_2 \ldots c_N]$. The l_i's are the outputs from each block in Figure 2, and $u(k)$, $y(k)$ are the linear plant input and output respectively. A is a lower triangular $N \times N$ matrix where the same elements are found respectively across the diagonal or every subdiagonal , b is the input vector, and c is the Laguerre spectrum vector. The vector c gives the projection of the plant output onto the linear space whose basis is the orthonormal set of Laguerre functions.

For a given linear plant there is an optimal pole a that minimizes the number of filters required to obtain a given accuracy for the model. The pole selection is a nontrivial problem which has been previously addressed in [29]. Since the model of the plant at crossover frequency is very important for the design of the closed- loop system, a good choice for the Laguerre pole will be in that frequency region. Here, the discrete Laguerre function pole a will be restricted to a fixed real value (0.25). This choice was made assuming that a proper sampling rate T has been selected within the controller. Because of its similarity to a Padé approximation, a Laguerre network with an adequate number of filters and the right pole is a very efficient way of approximating a dead time.

Equation 2 applies only to asymptotically stable, i.e. self-regulating systems. 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. The discrete time Laguerre network will then only model the stable part of the plant [28]. However, to design a predictive controller the model has to be first augmented to account for the disturbance.

IV. Model augmentation

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 are matching. To estimate the process output slope a batch least squares is used. If this slope is smaller than a given threshold the plant is then assumed to be at equilibrium, its input recorded as u_{eq} and learning started. The equilibrium value u_{eq} is removed from the true system input (i.e. $u(k) = u_{true}(k) - u_{eq}$).

The model states are updated based on:

$$\begin{aligned} l(k+1) &= Al(k) + Bu(k) \qquad (6) \\ l_f(k+1) &= A_f l_f(k) + B_f u_f(k) \\ l_d(k+1) &= A_d l_d(k) + B_d u_d(k) \end{aligned}$$

and further the output estimations are defined as:

$$\begin{aligned} \hat{y}(k) &= \hat{y}(k-1) + C(k)l(k) + \hat{y}_f(k) + \hat{y}_d(k) \qquad (7) \\ \hat{y}_f(k) &= \hat{y}_f(k-1) + C_f(k)l_f(k) \\ \hat{y}_d(k) &= \hat{y}_d(k-1) + C_d(k)l_d(k) \end{aligned}$$

where f denotes a feedforward variable and d a variable associated with the unmeasured disturbance model.

Following the extended Kalman filter approach, the input to the unknown disturbance model is estimated as:

$$\hat{u}_d(k) = (\hat{y}(k-1) + \hat{y}_f(k-1) + \hat{y}_d(k-1)) - y(k-1) \quad (8)$$

The estimation and the inclusion of the disturbance model in the overall prediction model is essential, especially when controlling integrating type systems due to their sudden departures from the nominal point when facing such abnormalities. Therefore the integration of the extended Kalman filter approach within the tool developed and presented in this paper becomes mandatory.

V. Practical predictive control

The concept of predictive control involves the repeated optimization of a performance objective (9) over a finite horizon extending from a future time (N_{P_1}) up to a prediction horizon (N_{P_2}) [30], [31].

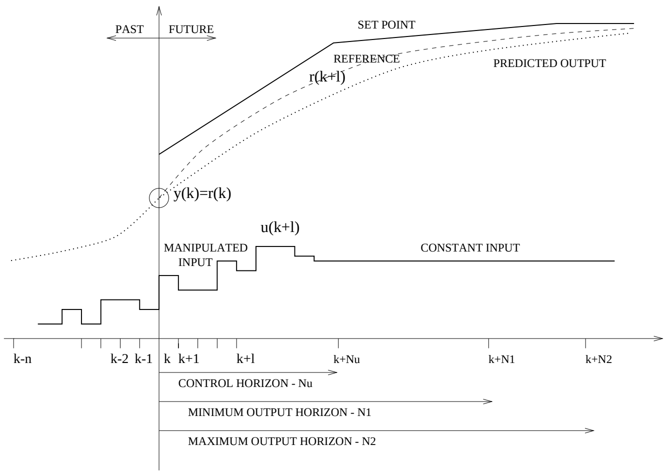

Fig. 3. The $MBPC$ prediction strategy

Figure 3 characterizes the way prediction is used within the $MBPC$ control strategy. Given a setpoint $s(k+l)$, a reference $r(k+l)$ is produced by filtering and is used within the following MBPC cost function (9):

$$J(k) = \sum_{j=N_{P_1}}^{N_{P_2}} \|(\hat{y}(k+j) - r(k+j)\|^2_{Q(j)} + \sum_{j=0}^{N_u-1} \|\Delta u(k+j)\|^2_{R(j)} \quad (9)$$

The minimization is performed subject to constraints on the:

- inputs levels: $u_l(k+j) \leq u(k+j) \leq u_u(k+j)$ where $0 \leq j \leq N_u - 1$
- input rates of change: $\Delta u_l(k+j) \leq \Delta u(k+j) \leq \Delta u_u(k+j)$ where $0 \leq j \leq N_u - 1$
- output levels: $y_l(k+j) \leq \hat{y}(k+j) \leq y_u(k+j)$ where $N_{P_1} \leq j \leq N_{P_2}$

Manipulating the control variable $u(k+l)$ over the control horizon (N_u) the algorithm drives the predicted output $\hat{y}(k+j)$, over the prediction horizon, towards the reference. In normal operation the weights $Q(j)$ and $R(j)$ are independent of k. For prediction it is assumed that $\Delta u(k+j) = 0$ for $j \geq N_u$. As formulated, the optimization is a quadratic programming (QP) problem, and can be solved using standard algorithms. In the absence of constraints, the problem reverts to a simple least squares (LS) problem

Here, we deal with a simplified version of the $MBPC$ algorithm to ensure real time implementation of the whole indirect adaptive scheme, based on a sampling time as low as 0.1 s. Addressing this issue was mandatory due to the wide range of applications, beyond process control, for which the controller was designed. As a result of this need, constraints are not managed through an optimization but using an anti-windup scheme, since it has been shown to have performance almost similar to constrained MBPC [32]. The main argument favoring the use of predictive control instead of a conventional state or output feedback control technique is its simplicity in handling varying time delays and non-minimum phase systems.

The simplified version is characterized by the fact that the N_{P_2} steps ahead output prediction is assumed to have reached the reference trajectory value $r(k+N_{P_2})$. Denoting the desired closed loop response in terms of the process time constant and delay (both expressed in a number of samples) by N_{min}, to guarantee stability of the control scheme $N_{P_2} \geq N_{min}$ is required. As long as this condition is satisfied and assuming that the ideal closed loop model on which our calculation were based does not violate other performance limitations, the inability of the predicted output to reach the reference should not be a cause for instability but for more active control movements.

As shown in Figure 3, a first order reference trajectory filter can be employed to define the N_{P_2} steps ahead setpoint for the predictive controller:

$$\hat{r}(k+N_{P_2}) = \alpha^{N_{P_2}} y(k-1) + (1-\alpha^{N_{P_2}})s(k))$$

This condition is not aimed at replacing the equality constraint used in most of predictive control stability proofs, it is just the result of choosing $N_{P_1} = N_{P_2}$, which implies that only one term is included in the cost function as far as the tracking error is concerned.

In other words we can write:

$$r(k+N_{P_2}) = \hat{y}(k+N_{P_2}-1) + \hat{y}_f(k+N_{P_2}) + \hat{y}_d(k+N_{P_2}) + +C(k)l(k+N_{P_2}) \quad (10)$$

Making the assumption that the future command stays unchanged: $u(k) = u(k+1) = \cdots = u(k+N_{P_2})$ (a condition equivalent to a choice for the control horizon of $N_u = 1$) then the output equal to the reference N_{P_2} steps ahead predictor becomes:

$$\begin{aligned} \hat{r}(k+N_{P_2}) &= y(k-1) + \hat{y}_f(k-1) + \hat{y}_d(k-1) + \\ &\quad \delta(k)l(k) + \delta_d(k)l_d(k) + \delta_f(k)l_f(k) + \\ &\quad \beta(k)u(k-1) + \beta_d(k)\hat{u}_d(k) + \beta_f(k)u_f(k) \end{aligned} \quad (11)$$

where

$$\begin{aligned} \delta(k) &= C(k)A^{N_{P_2}} \\ \delta_d(k) &= C_d(k)A_d^{N_{P_2}} \\ \delta_f(k) &= C_f(k)A_f^{N_{P_2}} \\ \beta(k) &= C(k)(A^{N_{P_2}-1} + \cdots + I)B \\ \beta_d(k) &= C_d(k)(A_d^{N_{P_2}-1} + \cdots + I)B_d \\ \beta_f(k) &= C_f(k)(A_f^{N_{P_2}-1} + \cdots + I)B_f \end{aligned}$$

Note that here $u(k)$ is unknown, $\hat{u}_d(k)$ (the estimated disturbance model input also known as the feedforward 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_{P_2} such that β is of the same sign as the process static gain and of sufficiently large amplitude. Therefore a possible criterion to be satisfied when choosing the horizon N_{P_2} is:

$$\beta(k) sign(C(k)(I-A)^{-1}B) \geq \epsilon |C(k)(I-A)^{-1}B| \quad (12)$$

with $\epsilon = 0.5$. Note that 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 identified models (i.e their Laguerre coefficients: $C(k)$, $C_f(k)$ and $C_d(k)$) are changing.

Solving the control equation (10) for the required control input $u(k)$ we have:

$$\begin{aligned} u(k) &= \beta(k)^{-1}(r(k+N_{P_2}) - \\ &\quad (y(k-1) + \hat{y}_f(k-1) + \hat{y}_d(k-1) + \\ &\quad \delta(k)l(k) + \delta_d(k)l_d(k) + \delta_f(k)l_f(k) + \\ &\quad \beta_d(k)\hat{u}_d(k) + \beta_f(k)u_f(k))) \end{aligned}$$

Accounting for the internal model principle the plant model needs to be augmented with an integrator for tracking ramps. Ramping signals as references are quite common in the case of batch reactors. Employing the integrator directly in the controller output while setpoint changes are encountered is a common practice:

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

where γ has an exponential characteristic such as to carefully account for a number of updates when the augmented integrator is active following a setpoint change, for improved performance. This controller has been designed for both self regulating and integrating processes, as well as step or ramping setpoints. To cope with this wide variety, and following the internal model principle (see [33] for more information) the above integrator is either included, or not in the loop, as appropriate. The initial state of this integrator is set at u_{eq}.

VI. The indirect adaptive predictive control solution

In model based control, the plant model has to be identified in order to produce a control action. Considering 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. As a result the proposed indirect adaptive control scheme uses a modified recursive least square (RLS) algorithm to estimate the parameters of the models involved in the control equation. RLS is used at each time step to obtain the parameter vector together with the covariance matrices. A good reference for the properties of the RLS is [34].

The use of a Laguerre network makes the parameter estimates less prone to bias caused by colored noise and unmodelled dynamics. To track time-varying parameters the standard RLS needs to be modified to ensure that the estimation gain does not converge to zero. Experience has shown that through the introduction of the two additional terms, μI and $\nu P(k)^2$, covariance matrix resetting and boundedness are achieved, see [35] [Theorem 3.4].

The core of the modified RLS algorithm is the update of the covariance matrix:

$$P(k+1) = \frac{1}{\lambda}\left[P(k) - \frac{P(k)l(k+1)l(k+1)^T P(k)}{\lambda + l(k+1)^T P(k) l(k+1)}\right] + \mu I - \nu P(k)^2 \quad (13)$$

where $\lambda \in [0,1]$ is the forgetting factor. This update is repeated in a similar manner for $P_f(k+1)$ and $P_d(k+1)$. Finally the parameter model estimates $C(k+1)$, $C_f(k+1)$ and $C_d(k+1)$ are updated as:

$$C(k+1) = C(k) + \frac{\alpha P(k) l(k+1)}{\lambda + l(k+1)^T P(k) l(k+1)} e(k) \quad (14)$$

This procedure is repeated, within the same C++ thread, in a similar manner, for the matrices of Laguerre coefficients: $C_f(k+1)$ and $C_d(k+1)$. In many cases, when dealing with an input type disturbance the $C_d(k+1)$ coefficients are fixed to reflect the plant dynamics. Typical values for the parameters used inside the estimator 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 persistent process excitation. The algorithm is expected to converge if the model error is small and the input signal is "rich" enough.

The learning procedure involves an update for the plant and known and unknown disturbance model state estimates (6). A flag priority mechanism is used to avoid the situation when two models are identified at the same time. This situation can lead to good global prediction but two unusable models for control. In fact, if later only one model is identified based on the other one being fixed, the results of the prediction based on such a model can lead to instability due to potentially high gains within the controller. Note that the unknown disturbance model can be fixed to a predefined value to reflect the types of expected disturbances. Finally, knowing the model states, we can update the plant and known and unknown disturbance model outputs based on (7).

Accounting for the unmeasured disturbances within the controller augments the novelty of the tool presented in this paper. Disturbances can enter the process at any point between the process input and output. In spite of this they can always be modelled as output disturbances. This is consistent with the extended Kalman filter approach. Hence, the main practical issue raised is the estimation of the sequence used as an input to the unknown disturbance model. For this an extended Kalman filter uses the $\hat{u}_d(k)$ as in (8) and $C_d(k)$ as in (14). In practice, at reset, the steps leading to the computation of $\hat{u}_d(k)$ are iterated a number of times for fast convergence.

A database of stable Laguerre state space representations for several first order plus dead-time systems was built and used during reset and startup procedures for the commercial controller.

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.

The advanced controller was implemented in C++ and runs on the Windows-NT operating system with a sampling time as small as 0.1 seconds for 32 loops simultaneously. An Object Linking and Embedding (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.

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 [28], [36] these issues are partially addressed.

VII. Industrial results

Under manual control, the skilled operator attempts to estimate the load and ensure a good temperature profile (PV) and therefore favorable reaction rates, via swings in the control variable (CV). This occurs at the expense of constant operator attention, product quality deterioration, the production of additional chemical components and therefore long batch cycles.

Figure 1 shows a PVC batch reactor under typical PID control. The batch temperature is controller by manipulating the setpoint of the jacket temperature control loop. This type of control implies that a rapid heating or cooling of the reactor mass is possible. Operating experience with PID control of the reactor made it necessary to use the cascade control configuration since the PID controller would require both a reduction of catalyst feed and an increase of cooling water to deal with high temperature excursions.

The *modus operandi* of this scheme requires that initially, under manual control, full heat is applied to the reactor to rapidly reach the desired reaction temperature. Before the latter is reached full cooling is applied for a predetermined time to prevent overshoot. The control is then transferred to the PID cascade system.

The results of this control strategy are presented in Figure 4. The temperature variation in the range of +/-5° F, creates a number of problems, as well an opportunity for advanced control.

Production capacity of the reactor is reduced whenever the cooling system is not providing maximum cooling as the exothermic reaction would cause the temperature to rise too high if the catalyst feed rate was also not reduced. It is therefore desirable that the cooling system remains at the maximum that the system can provide and then regulate catalyst feed to the highest possible rate possible provided that the temperature target is not exceeded. Temperature control would then be accomplished by simply adjusting catalyst feed rate.

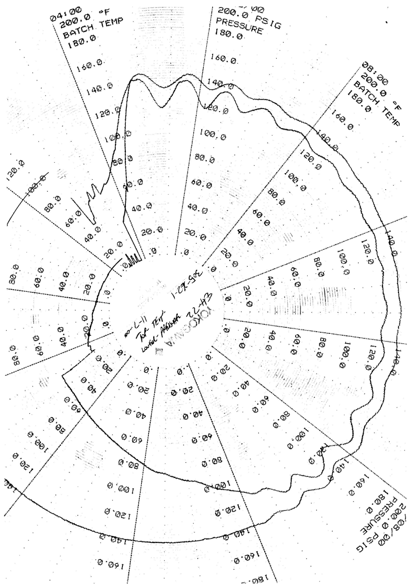

Fig. 4. The PVC batch reactor response under cascade PID control

Based on the successful operating experience with this adaptive controller on other processes, it was decided to use it on this reactor as illustrated in Figure 1. The model developed used 10 discrete Laguerre filters to accommodate the reactor time varying delay. The pole selection for the network was $a = 0.25$ for a sampling time of 1 minute.

The manual and PID control data available allowed for accurate initial model estimation, which significantly reduced the model building procedure. With the controller in manual mode, this model was implemented and learning switched on. After a bump test used for further learning and validation of this model the advanced controller was also turned on with a prediction horizon fixed at $N_{P_2} = 40$. As observed this horizon is far shorter than the batch time. The current controller does not assume high level optimization which will normally consider it. In exchange, the controller provided very accurate regulatory level control based on a setpoint generated externally. Additionally from the moment the application was completed onwards the controller was left in the loop with the learning switched on.

With the cooling system operating at maximum, the adaptive controller successfully controlled the reactor temperature to within +/- 2° F by adjusting catalyst feed rate (GPH). The stable temperature (DEGF) control allowed the reactor to produce PVC with a more consistent molecular weight, one of the primary quality parameters for PVC. However, the criterion for stopping the batch is quantity of monomer converted and not average molecular weight. An example of such batch results can be observed in Figure 5. Note the similarity between the actions taken by human operator vs. the controller. This gives further confidence that we should approximate such slow processes like batch reactions with integrating systems for adequate performance. Such approximations explain the average ramping of the feed rate between time intervals 10 and 34 followed by swings in the CV dedicated to disturbance rejection.

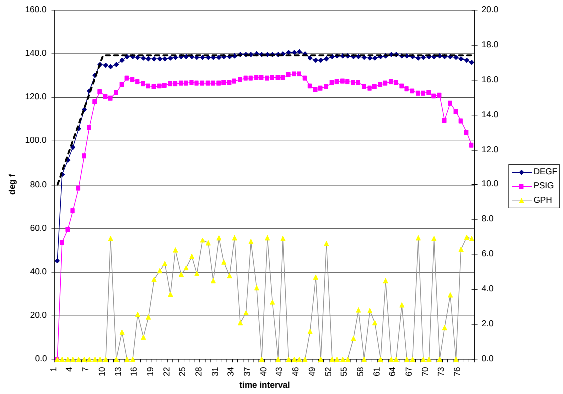

Fig. 5. PVC Reactor Batch Results (DEGF - degrees Fahrenheit, PSIG - pounds per square inch gauge, GPH - gallons per hour, time interval measured in tens of minutes, reference dashed)

In terms of tracking, the closed loop system exhibited minimal errors when facing plant challenges such as integrating disturbances and feedforwards (PSIG). Although the variations of the catalyst feed rate seem high, in fact the total consumption of catalyst has been reduced by 10% in comparison with the PID control.

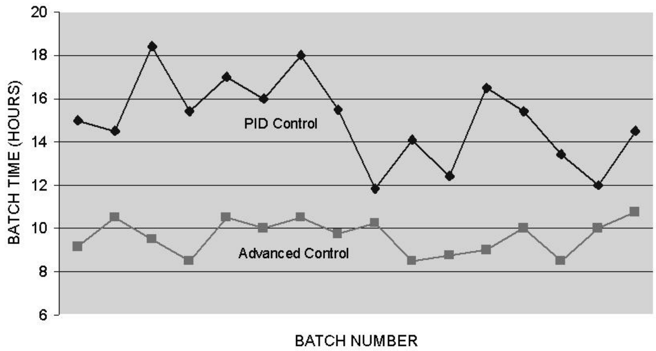

Fig. 6. PVC Reactor Batch Cycle Time Comparison

Batch cycle times for the PID controlled batches using the original control strategy would range from 12 to 18 hours, with a typical batch time of about 15 hours. The adaptive controller using the new control scheme was able to complete the same product batches in cycle times that ranged from 8.5 to 10.5 hours, with a typical batch time of about 9.5 hours. Hence, the batch cycle times were substantially reduced as shown in Figure 6.

The adaptive controller significantly improved the product quality while increasing the production capacity of the plant by 50%. This was not possible with the PID controller as it was not capable of maintaining adequate control of the reactor temperature by adjusting catalyst flow alone.

VIII. Conclusions

PVC batch reactors exhibiting long time constants and time delay can be regarded from the controller perspective and for improved performance, as integrating time delay systems.

A commercial adaptive predictive controller designed to cope with such challenging systems has been presented, emphasizing the modifications required to a standard algorithm to accommodate the identification in Laguerre domain of marginally stable systems. Also, the paper has presented an extended Kalman filter type approach to account for unmeasured self regulating or integrating disturbances in a predictive control framework.

The performance of the controller allowed a good tracking of the temperature profile for the PVC batch reactor which has, as a consequence, a significant reduction in the batch cycle with immediate savings for the company manufacturing such products. Since this initial application was completed, the present scheme has been applied to 25 batch reactors with similar results.

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