Simulation Study to Control Solids Flow Rate in a Pilot Scale Cold Flow Circulating Fluidized Bed

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Abstract—Controller scaling that is used to frequency-scale an existing PID controller for a large class of plants, eliminates the repetitive controller tuning process for plants that differ mainly in gain and bandwidth. Controller parameterization makes the controller parameters a function of a single variable, the loop-gain bandwidth, and greatly simplifies the tuning process. The controller is scaled according to the gain and frequency scales of the given plant transfer function and the bandwidth parameter whose initial value is set based on the bandwidth requirement from the transient response. This single parameter is required to be gradually adjusted according to a controller performance.

However, if the explicit transfer function of a given system is not known, the gain and frequency scales can be determined from an empirical model transfer function obtained from the System Identification procedure. In this paper, we propose a new technique based on the theory of Recursive Least Squares Estimation that allows determining the bandwidth parameter as well as the closed loop model parameters online. As the technique is recursive by nature, it further avoids the adjustment of a bandwidth parameter in accordance with the controller performance.

In a simulation study of controlling solids circulation rate, the technique is applied to time series data obtained from a pilot scale cold flow circulating fluidized bed (CFCFB) present at National Energy Technology Laboratory, Morgantown, WV. If the measurement of solids flow rate were possible as in the present cold flow model, the proposed method could be tested in an industrial scale system such as a fluidized catalytic cracking (FCC) reactor.

Keywords—PID, Tuning, Recursive Least Squares, Cold Flow Circulating Fluidized Bed, Solids Circulation Rate

I. INTRODUCTION

It is interesting to note that more than half of the industrial controllers in use today utilize PID control schemes. Many different types of tuning rules for controller parameters have been proposed in the literature, Ziegler et. al. [1], Åström et. al. [2]. This has moved from ad hoc tuning methods such as Ziegler and Nichols tuning tables to pole placement and frequency response. Also, automatic tuning methods have been developed and some of the PID controllers may possess online automatic tuning capabilities, Åström et. al. [3].

In Gao [4], the tuning of a PID controller is reduced to adjusting a single parameter known as the bandwidth optimization parameter, instead of three. Practical optimization, based on the controller’s performance, is incorporated into the one-parameter tuning. Effective tuning, however, is dependent on designing the PID control system with a good understanding of the plant under study and its operating environment.

However, in a number of instances, the plant to be controlled is too complex and the basic physical processes in it are not fully understood. Control design techniques then need to be augmented with an identification technique aimed at obtaining a progressively better understanding of the plant to be controlled. It is thus intuitive to aggregate system identification and control. If the system identification is recursive – that is the plant model is periodically updated on the basis of previous estimates and new data – identification and control may be performed concurrently.

In this paper, a technique of Recursive Least Squares Estimation (RLS) is applied to obtain an empirical model of the process and this model is used to design a PID controller with regards to a certainty equivalence property. The
bandwidth parameter of the controller is automatically adjusted.

The resulting controller is utilized in synchronization of two Lorenz systems. In a simulation study of controlling solids circulation rate, the technique is also applied to time series data obtained from a pilot scale cold flow circulating fluidized bed present at National Energy Technology Laboratory (NETL), Morgantown, WV.

In the circulating fluidized bed process, the mixing and reaction times are dependent upon the two primary parameters: the gas flow and the solids circulation rate. The solids circulation rate (SCR) is measured dynamically by Ludlow et al. [5] and the time variability is found to be very large relative to the time-averaged values, typically on the order of 50% of the steady state value. The system is currently under the action of PI control during operation. Ideally, the future controller objective should be to reduce these variations in solids flow rate to the smallest level possible, thereby narrowing the residence time distributions and improving the process operation.

In this work, the performance of an adaptive PID controller is tested by evaluating simulated results of solids circulation rate control. Data for this study was obtained by running the NETL cold flow circulating fluidized bed with the 60 microns glass bead bed material. This bed material belongs to Geldart Group A (Geldart [6]) and behaves similarly to that used in FCC reactors. The nature and variations of process variables with this type of bed is similar to that used in FCC reactors. The nature and variations of process variables with this type of bed is usually much more complex than those shown by Group B materials (cork as used in Koduru et al. [7] and Park et al. [8]).

II. AN ADAPTIVE PID CONTROL ALGORITHM

Consider a common controller design scenario shown in Fig. (1). Here, as suggested by Gao, the PID tuning parameters have been consolidated into the bandwidth optimization parameter, \( \omega_c \). Since the plant parameters are in fact unknown, they are estimated using a RLS algorithm. The controller parameter \( \omega_c \) is then obtained from these estimates of the plant parameters, in the same way as if they were the true values.

Let the plant be specified as

\[
A(q)y(k) = B(q)u(k) + C(q)v(k)
\]

where

\[
v(k) = \delta(k) + \eta(k), \quad A(q) = q + a(k), \quad B(q) = b(k), \quad C(q) = 1
\]

For this analysis, only a first order single input single output system is considered. Similar solutions for higher order multi-input single-output plants can be easily obtained, however. Here, \( q \) is the forward time shift operator and \( k \) is the discrete time index.

The model of the plant can be written as

\[
\hat{A}(q)y(k) = \hat{B}(q)\hat{u}(k)
\]

This gives

\[
\hat{y}(k) = \hat{G}_p(q)\hat{u}(k)
\]

where \( \hat{G}_p(q) \) is the estimated plant transfer function given as

\[
\hat{G}_p(q) = \frac{\hat{b}(k)}{q + \hat{a}(k)}
\]

In the controller design, \( \omega_c \) is selected as the measure of performance of the controller, [4]. \( \omega_c \) is denoted as the bandwidth of the feedback controller and \( \hat{G}_c(q, \omega_c) \) is the controller. Bandwidth parameterization also known as \( \omega_c \)-parameterization refers to assigning all closed-loop poles at \( -\omega_c \) and making all parameters of the controller a function of \( \omega_c \). Applying the simple pole-placement design to the first order plant (4), a \( \omega_c \)-parameterized controller is obtained as

\[
G_c(q, \omega_c) = \frac{\omega_c(q + \hat{a}(k))}{\hat{b}(k)q}
\]

making the closed loop transfer function

\[
\frac{\omega_c}{q + \omega_c}
\]

From Fig. (1), it is clear that

\[
u(k) = G_c(q, \omega_c)\hat{y}(k)
\]

Substituting the controller transfer function from Eq. (5) to Eq. (6) and manipulating, we obtain

\[
u(k) = \frac{\omega_c(e_k + \hat{a}_{k-1}e_{k-1})}{b_{k-1}}
\]

and

\[
u(k - 1) = \frac{\omega_c(e_{k-1} + \hat{a}_{k-2}e_{k-2})}{b_{k-2}}
\]

Substituting the value of \( u(k - 1) \) in Eq. (2) gives

\[
\hat{y}_k = -\hat{a}_{k-1}\hat{y}_{k-1} + \hat{b}_{k-1}u(k - 1) = -\hat{a}_{k-1}\hat{y}_{k-1} + \frac{\hat{b}_{k-1}\omega_c(e_{k-1} + \hat{a}_{k-2}e_{k-2})}{b_{k-2}}
\]

III. \( \omega_c \) ESTIMATION

The following cost function is minimized with respect to \( \omega_c \) at \( \omega_c = \hat{\omega}_c \).

\[
J_c = (v(k) - \hat{y}(k))^2
\]

This gives
\[ \hat{\theta}_k = \left( \hat{b}^T \hat{b} \right)^{-1} \hat{b}^T \ell_k \]  

where

\[ \hat{b} = \frac{\hat{b}_{k-1}}{b_{k-2}} (e_{k-1} + \hat{a}_{k-2}e_{k-2}) \]  

and

\[ \ell_k = r(k) + \hat{a}_{k-1} \hat{y}_{k-1} \]  

IV. SUMMARY OF ADAPTIVE PID CONTROL ALGORITHM

1. At \( k = 0 \), initialize \( \hat{a}_0, \hat{a}_{-1}, \hat{b}_0, \hat{b}_{-1}, \hat{e}_{-1}, \hat{y}_0 \) and \( P_0 \). Assume \( \lambda \).
2. At \( k = 1, 2, ..., N-1 \),
   a) \( \ell_k = r(k) + \hat{a}_{k-1} \hat{y}_{k-1} \)
   b) \( \hat{b} = \frac{\hat{b}_{k-1}}{b_{k-2}} (e_{k-1} + \hat{a}_{k-2}e_{k-2}) \)
   c) \( \hat{\theta}_k = \left[ \hat{\theta}_{k-1} \right]^T \)
   d) \( \hat{y}_{k-1} \)
   e) \( u(k-1) = \hat{a}_k \left( \hat{\theta}_{k-1} + \hat{\theta}_{k-1} \hat{y}_{k-1} \right) \)
   f) \( Q_k = \frac{P_{k-1}}{\lambda + \phi_k^T P_{k-1} \phi_k} \)
   g) \( K_k = Q_k \phi_k \)
   h) \( \hat{y}_k = \phi_k^T \hat{\theta}_k \)
   i) \( \hat{\theta}_k = \hat{\theta}_{k-1} + K_k \left( r_k - y_k \right) \) (a \( d \times 1 \) vector)
   j) \( P_k = \frac{1}{\lambda} \left( P_{k-1} - P_{k-1} \phi_k \phi_k^T P_{k-1} \right) \)
   k) \( \hat{a}_k \)
   \( \hat{b}_{k-2} = \hat{b}_{k-1}, \hat{b}_{k-1} = \hat{b}_k \)
   \( \hat{e}_{k-2} = \hat{e}_{k-1}, \hat{e}_{k-1} = \hat{e}_k = (r_k - \hat{y}_k), \hat{y}_{k-1} = \hat{y}_k \),
   \( \hat{\theta}_{k-1} = \hat{\theta}_{k-1}, P_{k-1} = P_k \)
3. Repeat steps (b) and (c) until \( k = N \).

V. ILLUSTRATIVE EXAMPLES

A. Synchronization of Chaotic Systems

The proposed control strategy was used to synchronize two chaotic Lorenz systems. These two systems can be represented as:

\[ \dot{x}_1 = \sigma (y_1 - x_1), \dot{y}_1 = r x_1 - y_1 - x_1 z_1, \dot{z}_1 = x_1 y_1 - b z_1 \]  

\[ \dot{x}_2 = \sigma (y_2 - x_2), \dot{y}_2 = r x_2 - y_2 - x_2 z_2, \dot{z}_2 = x_2 y_2 - b z_2 \]  

Since, the objective is to synchronize the outgoing signals \( y_1(t) \) and \( y_2(t) \), their difference can be used as a control signal. This is schematically illustrated in Fig. (2).

Fig. 2. Schematic representation of two chaotic systems synchronized.

To insure chaotic behavior, the parameter values for systems (14) and (15) are chosen as \( (r, \sigma, b) = (28, 10, 8/3) \).

Initial conditions for system (1) are \((x_1(0), y_1(0), z_1(0)) = (1, 0, 1)\) and for system (2), \((x_2(0), y_2(0), z_2(0)) = (1, 0, 0, 1, 1, 1)\), respectively. Since the motion on the attractor exhibits sensitive dependence on initial conditions, Strogatz [9], the control objective is to synchronize system (15) with respect to system (14) irrespective of the difference in initial conditions.

Fig. 3. Synchronization between \( y_1 \) and \( y_2 \). Black and red lines indicate \( y_1 \) and \( y_2 \) respectively. Blue line represents \( y_2 \) from system (16) with different initial conditions. Error between \( y_1 \) and \( y_2 \) are indicated by a black dashed line.

The discrete model for initial parameter estimation, and synchronization is defined as:

\[ \hat{y}_k^2 = \hat{\theta}_{k-1} \hat{y}_{k-1}^2 + \hat{\theta}_{k-1} (k-1) y_{k-1}^1 + \hat{\theta}_{k-1} \hat{y}_{k-1} \]  

and the reference signal \( r(k) \) is set to \( y_{k-1}^1 \). The numerical integration is carried out using a fourth order Runge-Kutta algorithm with a step size of 0.01. The controller is also simulated at the same step size.

The experimental results are shown in Fig. (3). The red curve indicates \( y_1 \), blue curve indicates \( y_2 \), and black curve hidden behind the red curve shows \( y_2 \) synchronized with \( y_1 \).

The error between \( y_1 \) and \( y_2 \) is represented by a black dashed line. Obviously, from the figure it is clear that \( y_2 \) is able to synchronize with \( y_1 \) nicely.
Another case involved the synchronization of chaotic Lorenz systems operated in a non-chaotic regime. Parameter values for this study are, Ho et al. [10], \((r_1, \sigma_1, b_1) = (28, 10, \sqrt{8/3})\) and \((r_2, \sigma_2, b_2) = (12, 6, 5)\). The initial conditions are \((x_1(0), y_1(0), z_1(0)) = (1, 0, 1)\) and \((x_2(0), y_2(0), z_2(0)) = (2, -1, 2)\). The control objective is to synchronize system (15) with respect to the system (14) irrespective of different parameter and initial values. Experimental plot in Fig. (4) depicts a successful synchronization of the signal \(y_2\) with \(y_1\). The blue line in Fig. (4) verifies that system (15) was not operated in a chaotic regime with the above parameter values and hence, the above control method is capable of synchronizing a system while operating in a regime other than chaotic regime with a chaotic system.

B. Control of a Cold Flow Circulating Fluidized Bed

![Diagram of CFB system](image)

The algorithm proposed in this paper was also used to simulate the control of solids flow rate in a circulating fluidized bed.

The schematic of the bottom portion of the NETL CFB is illustrated in Fig. (5). The mathematical model of the fluidized system based on a structural identification (the primary step of system identification) was derived as

\[
\hat{y}_k = -\hat{a}_{k-1}\hat{y}_{k-1} + \left[\hat{b}_1(k-1) \hat{b}_2(k-2) \hat{b}_3(k-1)\right] u_{k-1}
\]

where \(\hat{y}\) is the output solids circulation rate in Kg/s, \(u\) is the input vector consisting of a move air flow injected into the standpipe just above the entrance of an L-valve, the L-valve aeration and the high aeration at the base of the riser that causes solids to flow up the riser column. All the inputs are measured in m/s. A detailed description of the NETL test facility can be found elsewhere, [7], [8].

The 600 data points of glass beads data were generated during the operation of the CFCFB near the fast fluidized regime. The minimum fluidization \(U_{mf}\) velocity for the material is 0.86 m/s, and the packed bed and minimum fluidized gas voidage \(e_{pb}\) and \(e_{mf}\) are 0.372 and 0.421, respectively. The riser superficial gas velocity was kept at 3.66 m/s while the L-valve superficial gas velocity at the exit of the valve was 0.029 m/s. During this experiment, the standpipe’s aeration was varied sinusoidally. The period of that modulation was at 90 seconds and the amplitude resulted in a variation of superficial gas flow in the standpipe of 0.055 m/s.

Under the operating regime mentioned, the CFCFB behaved like a nonlinear chaotic system as can be seen by analyzing differential pressure fluctuation time series measured across the riser. Similar observations were made in Bai et al. [11] using FCC catalyst in the fast fluidized regime of their laboratory scale circulating fluidized bed. The solids circulation rate measured by a spiral vane placed in the packed bed portion of the standpipe ([5]), seems to demonstrate chaotic behavior as well, as depicted in Fig. (6). The simulation objective of this conceptualized strategy is to control the solids circulation rate to remove this chaotic behavior and leave only a smooth sinusoidal signal with a maximum value of 14.00 Kg/s.
The reference signal was generated from a solids superficial velocity, \( U_s \), that is obtained from an Knowlton's correlation Knowlton et al. [12], between the packed bed and fluidization condition, for a slip velocity between gas and solids and assuming solids travel faster than gas in the downward direction as follows:

\[
U_s = \frac{U_a}{e_{ave}} (1 - e_{ave}) + \frac{U_{mf}}{e_{mf}} (1 - e_{ave}) (e_{ave} - e_{pb}),
\]

\[
r(k) = \rho_p A_{SP} U_s,
\]

\[
e_{ave} = \frac{e_{mf} + e_{pb}}{2}
\]

\[
U_a = u_1 (\text{MoveAirFlow})
\]

Fig. 8. Manipulated riser superficial gas velocity (black solid line).

The initial values of the model parameters and the error values between measured and estimated output, are obtained from the historical input-output data by running the simulation for 50 seconds using the RLS algorithm on the multi-input single-output system (17) with a forgetting factor \( \lambda = 0.99 \). The simulated result is illustrated in Fig. (7). As can be seen from the figure, the two are almost indistinguishable. We conclude that for the given example high performance is achieved through the use of an adaptive PID controller.

With the above set point condition, the parameters were allowed to vary in order to reduce the variation in the SCR included the riser superficial gas velocity, the move air, and the L-valve aeration. Each of these controlling variables varied in a smooth continuous manner consistent with achievable time responses for the controllers. In addition, each varied in sinusoidal manner indicative of the imposed modulated move air flow. The predicted variations for the L-valve and move air flow were large yet achievable; however, variations in the riser flow were larger than physically practicable and therefore, limitations were required based upon influences on its dependence on solids fractions and inventories throughout the CFB-loop.

To overcome this physical limitation for the riser gas flow, the following constraints were applied during the simulation period:

\[
U_g = U_g^r, \text{ if } U_g (k) > \max(U_g^r), \text{ or } U_g (k) < \min(U_g^r)
\]

\[
U_{LV} = \frac{\min(u_2), U_g (k) \in \min(U_g^r)}{\max(u_2), U_g (k) \in \max(U_g^r)}
\]

where

\[
U_g^r (k) = \alpha \text{ normalized } \frac{r(k)}{A_{riser} \rho_p} + \beta u_3 (k)
\]

The normalization is carried out in the [0, 1] range and \( \alpha \) and \( \beta \) are chosen to be 0.8 and 0.96, respectively based on better matching results of the controlled SCR with the reference signal. \( u_2 \) and \( u_3 \) are the predetermined L-valve and riser superficial gas velocities.

The controlled SCR was simulated after utilizing the constraint in Eq. (19). The manipulated riser gas flow and move are depicted in Figs. (8), and (9), respectively. The required changes in each of these three variables were within readily achievable values and response rates. The independent aeration were maintained within achievable limits, even though they were somewhat large due to the relatively high solids circulation rate of 14 Kg/s. The move air was found to be shifted slightly in phase to better control the solids flow rate (Fig. (9)). The riser flow was varied within the constraints imposed upon it in a sinusoidal manner to compensate for the variations within the SCR (Fig. (8)). The L-valve aeration did not significantly affect the model and thus does not vary within the simulated controller (not shown). The dependence of solids circulation rate on L-valve aeration is also minimal when the unit is actually run.
The controlled SCR and the error between the set point and the controlled SCR are shown in Figs. (11). From Fig. (11), it is clear that controlled output matched nicely with the set point after about 60 seconds. The error between them shown lies within the acceptable range. The variation that was observed to be as large as 50% of the mean value (Fig. (6)) is reduced in the simulation by an order of magnitude less than 5% of the controlled value.

![Fig. 11. Controlled solids circulation rate (red solid line) after utilizing constraint (16) and reference solids circulation rate (black solid line).](image)

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we have proposed an adaptive technique for the PID control of plants whose mathematical models are not available. The method is based on the theory of Recursive Least Squares Estimation and allows determining the bandwidth optimization parameter that has reduced the tuning of a PID controller to adjusting a single parameter instead of three as well as the closed loop model parameters online.

Even plants, whose mathematical models exist, might be controlled for synchronization using this technique and a simple linear model rather than utilizing their state space equations. Synchronization of a chaotic system has been presented for the cases comprising of two Lorenz systems with different initial conditions and different parameter values. The method has been tested by simulating the control of the solids circulation rate using offline time series data generated from a benchmark CFB example (Stephanopoulos [13]), whose explicit physical model is not known. Experimental data was measured in the test facility that contained sensor noise and system disturbances. The variations in the solids flow rate were reduced to 5% at least in the simulation study. This may not be true in real life but it is believed that the performance would be better than the existing control strategy due to its adaptive nature.

In future, environmental, safety and process control requirements, Åström and Hägglund [14], as well as a stable pressure balance mechanism around a CFB loop and the constraints of maintaining air flows above certain limits must always be ensured while running the system under this scheme. Once these requirements could be satisfied in cold unit and if it is possible to come up with the way of measuring or estimating solids circulation rate in a hot pressurized environment, then the overall proposal could possibly be extended to the industrial set up.

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