An Iterative Learning Control Strategy for a Fedbatch Phenol Degradation Reactor

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Abstract. This paper presents an Iterative Learning Control strategy for a fedbatch phenol biodegradation process. One of the important features of the proposed approach is that it uses only a few off-line output measurements, circumventing the well-known drawback of insufficient on-line measurement capability in many *in situ* fermentation control applications. Since a zero-order hold input policy is shown to lead to misleading control results, the key technique was to generate the control profile with a piecewise continuous functional basis. Simulation results are presented to demonstrate the feasibility of the proposed ILC strategy.

1 Introduction

Mathematical modeling, identification and real-time control of phenol biodegradation processes, and of fermentation processes in general, represent a challenging area of endeavor for biotechnologists and control engineers, mainly due to the complexity of biological systems. The main goals in applying control methods to such living systems are to improve operational stability and degradation efficiency. As an area for control applications, the field of fermentation processes technology is still exhibiting a number of interesting characteristics that can challenge the efficiency of any control scheme. In fact, the control design for most biotechnological processes is made difficult by at least two well-known major factors [3]. First, the processes involving living organisms exhibit large nonlinearities, strongly coupled variables and often poorly understood dynamics. Second, real-time monitoring of many key process variables, which are needed in advanced control algorithms, is hampered by the lack of reliable on-line sensors.

The concern of phenol degradation, an hazardous pollutant contained in industrial wastewater from many chemical plants, oil refineries and agrochemistry plants, has been generating considerable research interest in technologies for biological treatment of industrial wastes [6]. Most of the currently used technologies are based on aerobic–activated sludge systems which are known to be sensitive

to fluctuations in the pollutant load, especially in the case of inhibitory or toxic substrates as phenol.

In this paper the attention is focused on *fedbatch* reactors, in which substrates or pollutants are fed either intermittently or continuously during the course of fermentation. This operating mode offers many advantages –at least from an industrial viewpoint– over batch and continuous cultures. The main advantage is concretely economical, since improved productivity may be obtained via providing controlled conditions in the supply of inhibitory substrates [10]. However, in contrast to continuous-flow reactors which operate continuously in steady-state, fedbatch reactors are permanently in a transient regime and therefore present challenging control design problems. Different trends for the design of monitoring and control algorithms for fedbatch fermentation processes have emerged, e.g. control approaches based on optimal [9] or adaptive [2] type arguments. The main drawback of the first trend is that model-based optimal control method, which provides a theorically realizable optimum under the assumption of a perfectly known model, could be dangerously misleading in a real-life implementation context due to the inherent uncertainty of the process dynamics and to the large variations of operating conditions. On the other hand, model-independent adaptive controllers do not guarantee *a priori* optimality of the control policy results. Finally, combining both trends, the approach based on the concept of *minimal modeling* of the kinetics, which does not suffer from the above difficulties, has emerged to fill the gap between modeling accuracy and control needs [3, ?]. In these references, it is also demonstrated how optimal -in the sense of optimal productivity- control of fedbatch processes could be replaced by a common nearly optimal regulation control case.

An Iterative Learning Control (ILC) strategy for a fedbatch phenol degradation process is investigated. The process model, which has been experimentally validated in [7] and [8], is used to illustrate that ILC is applicable to fedbatch fermentation processes. The choice of an ILC technique, justified by the repetitive nature of fedbatch cultures, is motivated by the following advantages upon standard control methods:

- since ILC uses information from previous executions of the task in order to improve tracking performance from trial to trial, it does not require any on-line measurement, and hence nor on-line sensor,
- the proposed ILC allows limited off-line measurement analysis to be carried out,
- ILC design is model-independent.

A preliminary evaluation of the optimal – or at least a good approximate– phenol concentration setpoint, which fixes the influent flow rate and the effective yield of phenol consumption, for the fedbatch reactor has been realized taking advantage of the prior modeling study presented in [7]. Due to the importance of achieving acceptable control performances over wide ranges of operating conditions and in the presence of potential uncertainties and/or disturbances, a practical applicable ILC controller that only needs off-line measurements of phenol concentration is proposed. Since in the case of large output sampling periods, zero-order hold

input profiles led to bad control behavior, piecewise continuous functions (linear and polynomial) are tested to reconstruct the input profile between samples.

The paper is organized as follows. In section 2, the phenol degradation process model is briefly described. The control objective is presented in section 3. The ILC control algorithms are presented and discussed in section 4, on the basis of a simulation study. A general conclusion ends the paper.

2   Process Modeling

In biotechnological processes, bacterial growth behavior is usually described by a set of non-linear equations derived from mass-balance considerations. The following equations describe the fedbatch phenol degradation by *Ralstonio euthropha*:

$$
\begin{aligned}
\frac{dX}{dt} &= \mu X - \frac{Q}{V} X \\
\frac{dS}{dt} &= -q_s X + \frac{Q}{V} \left(S_{in} - S \right) \\
\frac{dP}{dt} &= \nu_p X - \frac{Q}{V} P \\
\frac{dV}{dt} &= Q
\end{aligned}
\tag{1}
$$

where X is the biomass concentration (g/l), S is the phenol concentration (g/l), S_{in} is the influent phenol concentration (g/l), V is the working volume (l) and Q is the feed flow rate (l/h). P, which corresponds to the 2-hydroxymuconic semialdehyde (2-hms) concentration (a reaction intermediate of yellow color), was linearly correlated to the yellow coloration formation [7]. μ, q_s and ν_p are the specific growth rate, the specific rate of phenol degradation and the specific rate of yellow color formation, respectively.

Although the growth of micro-organisms depends on many environmental conditions (temperature, pH, mineral salts, etc.), the kinetic parameters generally express the dependence on the main process variables. Preliminary batch cultures have allowed the kinetic parameters to be established [7]. The growth behavior of *R. eutropha* has been studied in a previous work and the double effect of inhibition and limitation of phenol concentration has been modeled by an Haldane equation:

$$
\mu = \mu_{\max} \frac{S}{K_s + S + \frac{S^2}{K_i}}
\tag{2}
$$

It has also been shown that μ and q_s are correlated by a linear relationship:

$$
q_s = \mu/Y
\tag{3}
$$

and that the specific phenol degradation rate is expressed by:

$$
\nu_p = \alpha_1 \mu + \alpha_0
\tag{4}
$$

3   Control Objective

Fedbatch control problem is an optimal control problem. Since the objective of phenol degradation processes is to maximize the final quantity of phenol consumed in a minimal time, a global criterion may be given by:

$$J = \gamma_1 \int_0^{t_f} S_{in}(\tau) Q(\tau) d\tau - \gamma_2 S_f V_f + \gamma_3 S_0 V_0 - \gamma_4 \int_0^{t_f} d\tau \qquad (5)$$

where γ_1, γ_2, γ_3 and γ_4 are weighting coefficients, $S_0 V_0$ is the initial quantity of phenol, $S_f V_f$ is the residual quantity of phenol (generally equal to zero) and t_f is the shutdown time. This non-quadratic criterion and additional constraints in the process variables force to use techniques which involve iterations towards the optimum, based on Pontryagin's Maximum principle, Green's theorem or Dynamical Programming. These techniques are not well adapted to implement closed-loop control algorithms, but they allow to determine open-loop optimal profiles of process variables. However, optimal control is a very model-sensitive technique. It requires a complete knowledge of the process model, including an analytic expression for all specific rates, e.g. equations (2) to (4) for the phenol degradation process. However, in biotechnological applications this assumption is in practice never fulfilled and, moreover, even if the perfect process model could be available, real-life implementation is still hampered by the lack of reliable sensors suited to real-time monitoring of the process variables needed in the controller. For the phenol degradation process, besides a perfect analytical knowledge of the specific rates μ, q_s and ν_p, and corresponding parameters, the control requires on-line measurements of all state variables X, S, P and V.

A more realistic and practical solution consists in implementing closed-loop controllers which regulate one –if possible– process variable. The aim of such *sub-optimal* solution is to replace the given optimal problem by a more common regulation problem. This standard regulation problem can then be solved by any feedback control loop, e.g. a fedbatch PI control of phenol degradation in [8] or adaptive linearizing control of Penicillin G production in [11]. As in any standard feedback control procedure, at least one on-line measurement or on-line estimation of process variable was required in all these studies.

In the case of phenol degradation by *R. eutropha* in fedbatch fermentations, it has already been shown [7, 8] that the control objective, corresponding to the maximization of the phenol degradation rate, may be stated in terms of phenol regulation to some *sub-optimal* setpoint (i.e. $S^r = 0.1g/l$). In the proposed ILC design strategy, only off-line analysis of phenol concentration are required. Thus, this approach may be considered as being in between the classical closed-loop controls and the open-loop systems commonly used in industrial fedbatch fermentations because of the lack of reliable on-line sensors. The feed flow rate $Q(t)$ corresponds to the control input of the system.

4 Iterative Learning Control

In fedbatch fermentations for phenol degradation, the task is executed in a finite time interval while the same task will be operated repeatedly. In such a case, the idea of *iterative learning control* is clearly applicable to improve the control performances of phenol degradation processes from run to run.

It should be pointed out that the ILC is not an open-loop control operation, although the ILC only modifies the input command for the next repetition [1]. ILC is closed-loop in repetitions since updates are performed for the next repetition using the feedback measurements of the previous repetition, as opposed to the closed structure of conventional controllers in time which updates the control signal of the next time step using the feedback at current or past time steps.

Let an operation of the phenol degradation system to be controlled be denoted by subscript i and let time during a given trial be denoted by t, where $t \in [0, N]$. The usual way to implement ILC is to use the following updating formula for the input signal $u_i(t)$ [5]:

$$u_{i+1}(t) = H(q)(u_i(t) + L(q)e_i(t)) \tag{6}$$

where $H(q)$ and $L(q)$ are linear filters, not necessary causal, $e_i(t)$ is the output tracking error and q the is the delay operator in the i-direction.

4.1 First-order ILC Algorithm

The first form of ILC selected for the phenol degradation system corresponds to the following P-type, in the i-direction sense, updating formula [5]:

$$Q_{i+1}(t) = Q_i(t) + k_p e_i(t) \tag{7}$$

where k_p is the learning gain and the control error is defined as $e_i(t) = S^r - S_i(t)$, S^r being the phenol setpoint.

Model simulation. The numerical values used for model simulation are $\mu_{max} = 0.41h^{-1}$, $K_s = 0.002g/l$, $K_i = 0.35g/l$, $Y = 0.68$, $\alpha_0 = -0.085$ and $\alpha_1 = 13$. The feeding phenol concentration is set to $S_{in} = 50g/l$, while initial conditions were $X(0) = 0.2g/l$, $S(0) = 0.15g/l$, $P(0) = 5g/l$ and $V(0) = 0.2l$.

It should be emphasized that the phenol degradation model presented in this work, which was previously validated by experimental batch data, is used to illustrate the applicability of ILC to phenol degradation using fedbatch systems.

Figure 1 illustrates the control error and input evolution in the i direction for two sampling periods $T_1 = 0.5h$ and $T_2 = 1h$. As shown in this figure, a zero-order hold input policy has not resulted in acceptable control performance. This occurrence can easily be explained by the fact that the substrate feedback control goal for fedbatch fermentation processes consists in *keeping an inherently unstable type of behavior under control* [3, 11], generally resulting in time-varying profiles of the actual process input, i.e. the feed flow rate $Q(t)$. Hence, freezing the control input during a too large period of time comes against its natural

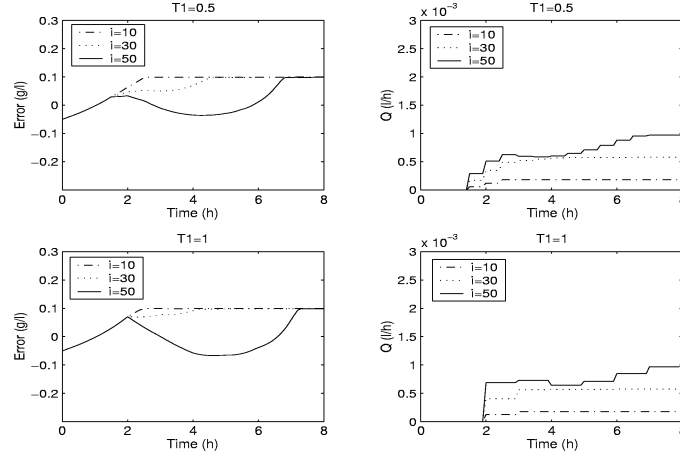time-varying behavior and could lead, as shown in the simulation results, to misleading control trajectories.

Fig. 1. First-order ILC for $T_1 = 0.5h$, $T_2 = 1h$; input and error evolution (zero-order hold case).

In this context, the idea of using some interpolation method in order to reconstruct a continuous input profile between two sampling period arises to circumvent this kind of problem. Besides, the fact of maintaining a large measurement period, instead of simply reducing it, is justified by the important economic aspect of minimizing the number of off-line phenol analysis –and consequently, the operator availability- in a real-life *in situ* implementation. In Figure 2, simulation results are illustrated for cubic-polynomial piecewise continuous function for input interpolation. Improved convergence behavior is obtained, although faster transient responses correspond to the shorter sampling period $T_1 = 0.5h$. A residual oscillation is present on both the error and the input $Q(t)$ evolution. In order to improve this kind of convergence characteristic, a P-type ILC approach that takes into account the next step, in the time direction sense, is investigated.

4.2   Arimoto P-type ILC Algorithm

The second form of ILC corresponds to the Arimoto P-type algorithm [1] updating formula:

$$Q_{i+1}(t) = Q_i(t) + ke_i(t+1) \tag{8}$$

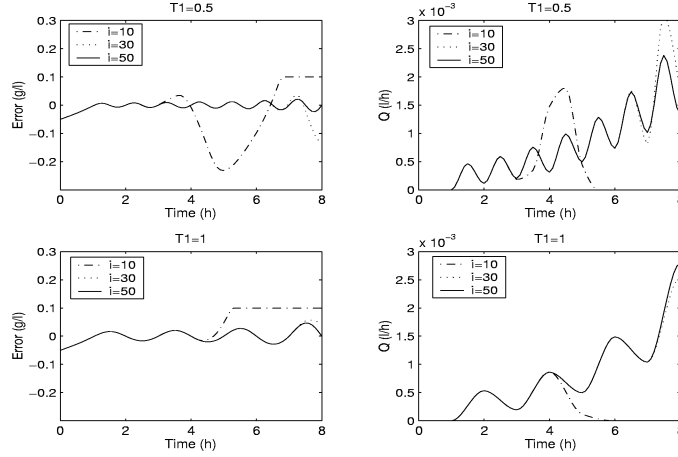where k is the learning gain.

Fig. 2. First-order ILC for $T_1 = 0.5h$, $T_2 = 1h$; cubic input interpolation.

Figure 3 illustrates the control error evolution in the i-direction using cubic polynomial input interpolation for different sampling periods $T_1 = 0.5h$ and $T_2 = 1h$.

As shown in Figures 2 and 3, the difference between the first-order ILC and the Arimoto P-type ILC control performances is significant. The P-type ILC algorithm has demonstrated improved robustness to regulate the phenol concentration at the end of the culture, i.e. when the control input Q is much higher according to its exponential profile. At the present, the convergence of the ILC algorithms using an interpolation technique between samples is being studied. Preliminary results seem to be similar to those presented in [4] for a classical ILC.

4.3 Variable sampling time

In order to minimize the off-line laboratory analysis, a preliminary study was carried out with a reduced number of samples that were strategically chosen on the basis of the process knowledge. As the ILC approach is closed-loop in the i-direction but not in time, a periodic sampling time is not required.

From the expert knowledge of the process, it was deduced that the control action is significantly more important at the end of the fermentation. Since this shutdown time is known in the context of fedbatch fermentations, three sampling points were chosen at the end of the culture (i.e. 6h, 7h and 8h), one when S^r is reached for the first time (i.e. 1h) and one at the middle of the fedbatch fermentation (i.e. 4h). Figure 4 shows the ILC P-type control and error evolution for these variable sampling points. Relatively good ILC convergence was obtained although the i-iteration transient convergence is a little slower when compared to the results of section 4.2, e.g. the Figure 4 shows that convergence is not garantied
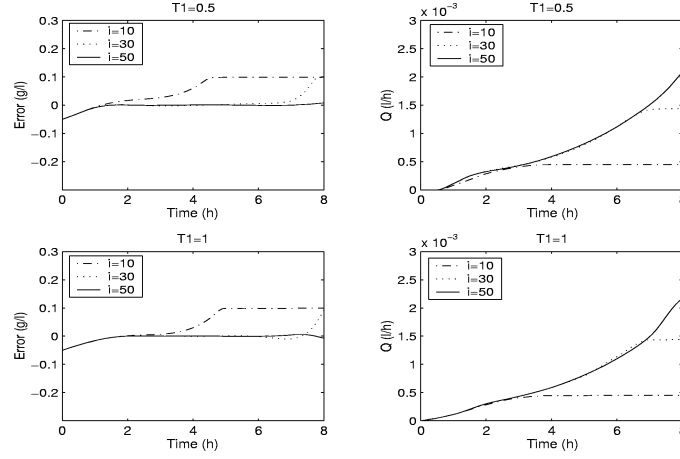
Fig. 3. P-Type ILC for $T_1 = 0.5h$, $T_2 = 1h$; cubic input interpolation.

yet at iteration $i = 30$. These preliminary results show the applicability of the proposed approach. Further studies concerning the convergence of the algorithms are in process.
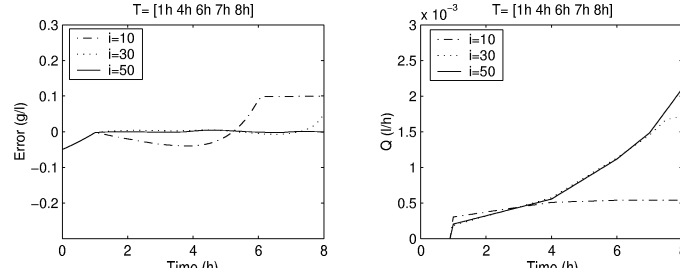

Fig. 4. P-Type ILC for variable sampling period T; input and error evolution.

5 Conclusions

A first-order and the Arimoto P-type ILC algorithms for phenol degradation in fedbatch fermentations were considered. Pre-evaluation of a nearly optimal phenol setpoint for fedbatch cultures led to the design of an easy-to implement ILC regulation problem. Due to misleading control performances in the case of zero-order hold input policy, the feed flow rate profile was modified using piecewise

continuous functions between samples. Simulation studies shown that the P-type ILC and large off-line measurement periods are sufficient to drive the output error to converge to zero after a relatively low number of iterations. Finally, the preliminary results of a variable sampling time strategy were presented, showing the applicability of this ILC strategy to fedbatch fermentation processes.

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