NONLINEAR BATCH REACTOR TEMPERATURE CONTROL BASED ON ADAPTIVE FEEDBACK-BASED ILC

Eduardo J. Adam[1]

[1]Facultad de Ingeniería Química, Universidad Nacional del Litoral, Santa Fe, Argentina

ABSTRACT

This work presents the temperature control of a nonlinear batch reactor with constrains in the manipulated variable by means of adaptive feedback-based iterative learning control (ILC). The strong nonlinearities together with the constrains of the plant can lead to a non-monotonic convergence of the l_2-norm of the error, and still worse, an unstable equilibrium signal $e_\infty(t)$ can be reached. By numeric simulation this works shows that with the adaptive feedback-based ILC is possible to obtain a better performance in the controlled variable than with the traditional feedback and the feedback based-ILC.

KEYWORDS

Batch reactor, Adaptive control, PID control, ILC

1. INTRODUCTION

Batch processes have received important attention during the past two decades due to incipient chemical and pharmaceutical products, new polymers, and recent bio-technological processes. The control of such processes is usually given as a tracking problem for a time-variant reference trajectories defined in a finite interval. Usually, the engineers talk about that a batch process has three operative stages clearly different, startup, batch run and, shutdown. While these three stages are widely studied by the engineers for each particular batch process, it is important to remark that in a widely number of cases, the most industries have managed to successfully operate these processes, but this operation is clearly far from optimal. Only with the experience of operators and engineers and, the repeated runs can be improved the operation control and the product quality.

Thus, one aspect of batch operation unexplored is how the control engineer can use repetitive nature of the operation to reach a better performance in the controlled variable. And, this is exactly the central point in which ILC theoretical framework is supported.

ILC associates three interesting concepts. *Iterative* refers to a process that executes the same setpoint trajectory over and over again. *Learning* refers to the idea that by repeating the same thing, the system should be able to improve the performance. Finally, *control* emphasizes that the result of the learning is used to control the plant.

For this reason, ILC constitutes the adequate theoretical framework to renew efforts in order to study new alternatives for the batch process control.
The first contribution to ILC was introduced by Uchiyama [24]. Since then, ILC has received considerable attention in the automatic control community. Important contributions to the ILC

DOI : 10.5121/ijics.2015.5101

theory appeared with [3], [5], [6], among others. The main idea behind the ILC technique is to use the previous trail information to progressively reach a better performance with every new iteration.

Thus, ILC has shown to be appropriate in processes whose operation is repeated over an over again, and it found a strong application field in the robotics area because of the repetitive nature of robot operations. Accordingly, interesting application examples are presented in the literature such as those of [3] and [9], among others. Afterwards, other authors [13], [14], [11] and [12]) extended this idea to industrial batch processes in chemical engineering for the same reason.

While, several authors obtain interesting results when the ILC scheme is implemented in real processes ([3]; [11]; [12]; [8]; among others), ILC can reach unsatisfactory results when the nonlinearities are strong, due to in many cases the linearities hypothesis cannot be sustained. In order to avoid a possible poor performance, [1], [2] and, [18] proposed to include an optimal learning algorithm to achieve a reduction of the l_2-norm of the error at each trail.

On the other hand, the idea of combining adaptive control with ILC was presented by several authors [7]; [22]; among others) especially with robotics applications but, outside of chemical engineering research. This paper present an adaptive feedback-based ILC scheme applied to a batch reactor with acceptable results where the l_2-norm of the error is reduced at each trail and an almost monotonic convergence is achieved.

The organization of this work is as follows. Next section presents the non-linear batch reactor here studied. Section 3 an Adaptive PI control is implemented. Section 4 includes a theoretical framework presentation related to adaptive feedback-based ILC scheme here studied. Then, Section 5 presents by means of numeric simulations the behavior of the batch reactor in closed loop when the designer pretends to apply the adaptive ILC linear theory to a nonlinear system. Finally, in Section 6 the conclusions are summarized.

2. NON-LINEAR BATCH REACTOR

Consider a batch reactor with a nonlinear dynamic where an exothermic and irreversible second order chemical reaction **A** → **B** takes place. It is assumed that the reactor has a cooling jacket whose temperature can be directly manipulated. The goal is to control the reactor temperature by means of inlet coolant temperature. Furthermore, the manipulated variable has minimum and maximum constrains. That is, $T_{c\min} \leq T_c \leq T_{c\max}$, T_{cmin} = -10, $T_{c\max}$ = 20 and, T_c is written in deviation variable.

So as to clarify the understanding of this work, the dynamic equations and the nominal values of the batch reactor are included in this section.

The reactor dynamic is modelled by the following equations:

$$\frac{dc_A}{dt} = -k_0 e^{-ER/T} c_A{}^2 \quad , \tag{1}$$

$$\frac{dT}{dt} = -\frac{\Delta H}{Mcp} k_0 e^{-ER/T} c_A{}^2 - \frac{UA}{Mcp}(T - T_c) \quad . \tag{2}$$

Also, it must be noted that the reaction rate kinetic is $r_A = kc_A{}^2$ with $k = k_0 e^{-E/RT}$ and the nominal batch reactor values are summarized in Table 1 and, they are based on data from literature [13].

Table 1. Nominal batch reactor values.

parameter	nomenclature	value
feed concentration	c_{Ae}	0.9 mol m^{-3}
feed temperature	T_e	298.16 K
inlet coolant temperature	T_c	298.16 K
heat transfer term	UA/Mcp	0.0288 l min^{-1}
reaction rate constant	k_0	4.7 10^{+19} l mol^{-1}s^{-1}
activation energy term	E/R	13550 K^{-1}
heat reaction term	$\Delta H/Mcp$	-5.79 K l mol^{-1}

A simple test was applied for determining of the linear transfer function parameters. This test consists of introducing a step change in cooling jacket temperature (manipulated variable) and the reactor temperature time response is registered. This numerical experiment is showed in Fig. 1 and the nonlinearity of the batch reactor is clearly evidenced.

In Fig. 1, the reader can notice that the transfer function structure of the batch reactor changes according to operation point of the reactor. For 28°C ≤ T_c < 31°C a good linear approximation is a first order plus zero while, for 31°C ≤ T_c < 32°C a better approximation is a simple first order. Thus, by simplicity and taking into a account that the batch reactor operates around 30°C, a first order transfer function was accepted as a first approximation to tune the controller parameters explained in the next section. Consequently, the transfer function parameters were computed using a Matlab optimization toolbox based on a multiparametric optimization algorithm. Accordingly, they result to be, the gain process K = 1, and the time constant T = 1.4370.

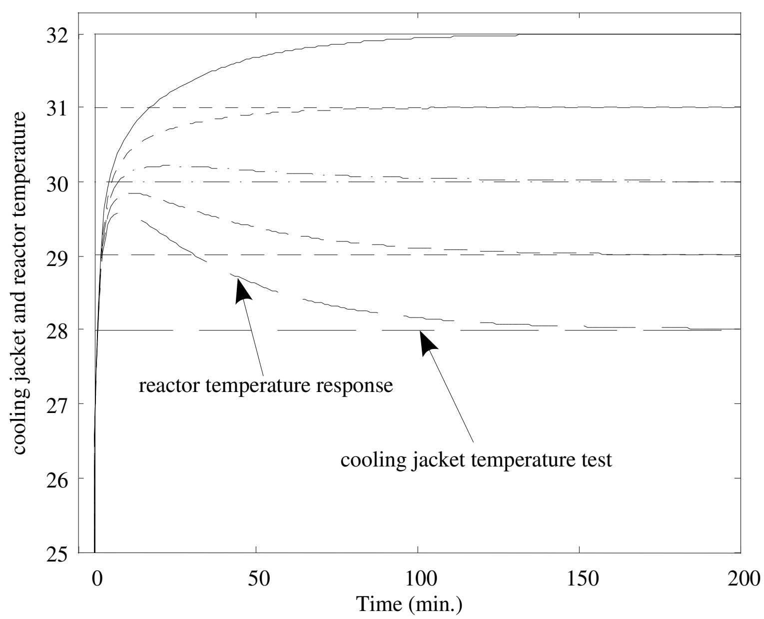

Figure 1. Batch reactor identification tests for different step changes in the cooling jacket temperature.

3. ADAPTIVE PI CONTROL

In this work, firstly, it is proposed to combine an on-line parameter identification of the plant in order to implement an adaptive PI controller. The classical literature ([4]; among others) presents two schemes clearly different to implement adaptive control, one of these is i) the Model Reference Adaptive Control (MRAC) and the other one is ii) the Self-Tuning Regulator (STR).

Due to the necessity to obtain on-line process data for the implementation of the ILC (presented in Section 4), it took advantage of these data to implement a STR scheme.

As for the identification procedure, the algorithms used for the on-line parameter estimation are the extreme importance. Here, it is considered that the system is perfectly deterministic and there are no disturbances and noises.

Now, consider the model,

$$y(k)+a_1y(k-1)+\cdots+a_ny(k-n)=b_1u(k-d-1)+\cdots+b_nu(k-d-n) \quad , \tag{3}$$

it is possible to write in a vectorial form,

$$y(k)=\psi^T(k)\theta \quad , \tag{4}$$

where

$$\psi^T(k)=[-y(k-1),-y(k-2),\cdots,y(k-n),u(k-d-1),\cdots,u(k-d-n)] \quad , \tag{5}$$

and

$$\theta=[a_{1,}\,a_{2,}\cdots,a_n,b_{1,}\,b_{2,}\cdots,b_n] \quad , \tag{6}$$

Then, $2n$ parameters must be found, and in consequence, $2n$ data of $u(k)$ and $y(k)$ are necessary. Thus, a linear equation system can be written where a_i and b_j are unknown parameters. That is,

$$\begin{aligned} y(k)&=\psi^T(k)\theta \\ y(k+1)&=\psi^T(k+1)\theta \\ \vdots &= \vdots \\ Y_k&=\Psi_k^T\,\theta \end{aligned} \tag{7}$$

or well,

$$Y_k=\Psi_k\,\theta \tag{8}$$

where $N=2n$,

$$\Psi_k=[\psi^T(k),\psi^T(k+1),\cdots,\psi^T(k+N-1)]^T \tag{9}$$

and Y_k = [$y(k)$, y(k+1), …, y(k+N-1)]^T. Then, the solution of (8) is given by,

$$\theta=\Psi_k^{-1}Y_k \tag{10}$$

As a particular case, considering the transfer function of the reactor indicated in the Section 2 then, the (3) has two parameters to estimate, that is, a_1 and b_1. In consequence, the vectors $\psi^T(k)$, Ψ_k ,and θ result to be,

$$\psi^T(k)=[-y(k-1),-u(k-1)] \tag{11}$$

$$\Psi_k=[\psi^T(k),\psi^T(k+1)] \tag{12}$$

and

$$\theta=[a_{1,}\;b_1]^T \quad . \tag{13}$$

Finally, based on a_1 and b_1 it is possible to calculate K and T by means of the following expressions,

$$K=b_1/(1-a_1) \quad . \tag{14}$$

and

$$T=-T_s/\ln a_1 \tag{15}$$

where T_s is the sample time.
Finally, based on the estimated parameters, it is possible to tune on line the controller parameters following a criterion for controller design. In this work, the PI controller was designed via optimal control theory as it is shown in the next subsection.

3.1. The Adaptive PI Implemented

The performance at steady state is extreme importance in the process control, i.e., the control system ability to absorb disturbances without leaving the desired operating point or, reach without error new steady state operating points.

Also, the classical literature ([17], [20] among others) presents alternative which combine an optimal design by state feedback and offset elimination.

A new fictitious state ξ is added to a linear system under state space representation (A, B, C) (but keeping the linearization around a fixed point) and, an augmented linear system can be defined as,

$$\begin{pmatrix} \dot{x} \\ \dot{\xi} \end{pmatrix} = \begin{pmatrix} A_k & 0 \\ -C_k & 0 \end{pmatrix} x(t) + \begin{pmatrix} B_k \\ 0 \end{pmatrix} u(t) + \begin{pmatrix} 0 \\ 1 \end{pmatrix} r(t) \quad . \tag{16}$$

where is defined

$$\dot{\xi} = r(t) - y(t) = r(t) - Cx(t) \quad . \tag{17}$$

Here, k denote that A_k, B_k and C_k are updated at each sample time.
For this system and holding the traditional cost function given by algebraic Ricatti equation (ARE), the resulting PI control law is

$$u = -\hat{K}\,\tilde{x} = -k_p x(t) + k_i \xi(t) \quad . \tag{18}$$

where $\hat{K} = R^{-1}\hat{B}_k{}' \hat{P} = \begin{bmatrix} K & k_i \end{bmatrix}$, $K = k_p$, $\tilde{x} = \begin{pmatrix} x(t) \\ \xi(t) \end{pmatrix}$, with states $x(t)$ coming from the real process

and $\hat{P}$ a solution of the ARE written with the extended linear system

$$\hat{A}_k = \begin{pmatrix} A_k & 0 \\ -C_k & 0 \end{pmatrix} \text{ and } \hat{B}_k = \begin{pmatrix} B_k \\ 0 \end{pmatrix} \quad .$$

Notice that, the PI control law has time variant modes as a result of solving a infinite-horizon optimal control problem in each time interval according to identified parameter of the plant in each instant.
Thus, the following procedure was implemented:

Design Procedure 1:

- Step 1. Using sample data, compute $\psi^T(k)$ and Ψ_k according to Eqs. (5) and (9) or well, for a simple case by using Eqs. (11) and (12).
- Step 2. Compute θ with Eq. (10) and then, compute $\hat{A}_k$ and $\hat{B}_k$ and at each sampling time.
- Step 3. Finally, compute the PI controller parameters k_p and k_i.
- Step 4. If $t = T_f$ with T_f the final time for the batch reactor operation then, stop the algorithm; the otherwise, increment the k-time and go to step 1.

4. LEARNING CONTROL APPLIED TO BATCH PROCESSES

4.1. The Basic Idea of the Adaptive ILC

The ILC scheme was initially developed as a feedforward action applied directly to the open-loop system ([3], [10]). However, if the system is integrator or unstable to open loop, or well, it has wrong initial condition, the ILC scheme to open loop can be inappropriate. Thus, the feedback-based ILC has been suggested in the literature as a more adequate structure ([19], [15], [21], [23]).

In this work, a traditional self-tuning regulator (STR) is combined with feedback-based ILC and, the basic idea is shown in Fig. 2

Notice that, in the block diagram of Fig. 2 it is possible to distinguish three blocks related to: i) data acquisition and parameters estimation of the plant, ii) adaptation mechanism for the controller design and iii) the controller with autotuning parameters.

This scheme operates as follows. Consider a plant, which is operated iteratively with the same setpoint trajectory over and over again, as a robot or an industrial batch process. During the i-th trail an input-signal $u_i(t)$ is applied to the plant, producing the output signal $y_i(t)$. Both signals are stored in the memory devise. Thus, two vectors with length T_f are available for the next iteration. If the system of Fig. 2 operates to open loop, using u_i(t) in the i+1-th trail it is possible to obtain the same output again. But, if the i+1 iteration includes $u_i(t)$ and $e_i(t)$ information then, new $u_{i+1}(t)$ and $y_{i+1}(t)$ can be obtained. The importance of the input-signal modification is to reduce the tracking error as the iterations are progressively increased. That is, $\|e_{i+1}\| \leq \|e_i\| \forall i \geq 0$. Thus, the purpose of an ILC algorithm is to find a unique equilibrium input signal $u_\infty(t)$ which minimizes the tracking error.

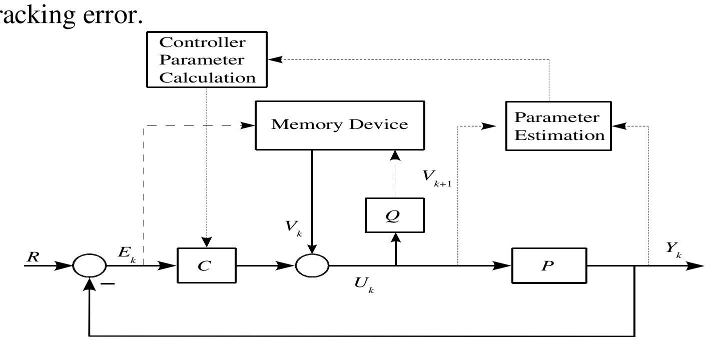

Figure 2. Schematic diagram of STR combined with feedback-based ILC. Here, continuous lines denote the signals used during the k-th trail, dashed lines denote signals will be used in the next iteration and doted lines belong to STR scheme.

Due to the existing strong nonlinearities in the chemical systems, the ILC scheme by itself cannot lead to a monotonic decrease of the error (in many cases). For such reason, an adaptive scheme is added in order to obtain a stable decreasing error l_2-norm of the error at each trail as it shows in the next section. The STR scheme here implemented follows the traditional recommendations given by classical authors as [4], among others.

4.2. The Tracking ILC Formulation

The ILC formulation uses an iterative updating formula and the most common algorithm suggested by several authors ([3], [9], [5], [23] among others) is given by

$$V_{i+1} = Q(V_i, + CE_i) \tag{19}$$

where $V_1 = 0$, C denotes the controller transfer function and Q is a linear filter[1].
A major issue in ILC is the convergence, and each type of ILC has its own convergence criterion. The tracking error $e_i(t)$ is defined as

$$e_i(t) := r(t) - y_i(t) \tag{20}$$

where the subscript i denotes the run number and e_i represents (finite-length) output error trajectory for i-th trail.
The idea is to find an input trajectory u_k which minimizes the output error,

$$\| e_i \| \rightarrow \varepsilon = \min_u \|e\| \tag{21}$$

as $i \rightarrow \infty$, where $\| \ \|$ is some vector norm.

Clearly, ε is a inferior level to be reached by feedback based-ILC as i-index is increased.

DEFINITION 1. *The feedback based-ILC system is said to have monotonic convergence if*

$$\forall i \geq 0: \ \varepsilon \leq \| e_{i+1} \| \leq \| e_i \| \tag{22}$$

Then, the tracking error $e_\infty(t)$ is an equilibrium signal reached by the control system if the system has this error signal for all future trails.
DEFINITION 2. *The equilibrium signal $e_\infty(t)$ is said to be stable if*

$$\forall B > 0, \exists b > 0, \|e_0(t) - e_\infty(t)\| < b \quad => \forall k \quad 0, \|e_k(t) - e_\infty(t)\| < B \ , \tag{23}$$

where $e_0(t)$ *is the initial tracking error.*
Definition 3. *An equilibrium signal $e_\infty(t)$ is said to be asymptotically stable if it is stable and*

$$\exists b > 0, \|e_0(t) - e_\infty(t)\| < b \quad => \quad \lim_{i \to \infty} \|e_i(t) - e_\infty(t)\| = 0 \tag{24}$$

The definitions presented before can be founded in the literature ([5], [16]).
Notice that, there exists a unique input $u_\infty(t)$ that yields the desired output $r(t)$, with a minimum tracking error $e_\infty(t)$.

4.3. A Simple Iterative Updating Formula

Now, Fig. 2, $U_i = V_i + CE_i$. Then,

$$V_{i+1} = QU_i \tag{25}$$

is a simple update formula in Laplace domain. Thus,

$$E_{i+1} = S(1 - Q)R + SQE_i \tag{26}$$

Being $E_{i+1} = R - Y_{i+1}$ then,

$$E_{i+1} = R - Y_{i+1} = R - PU_{i+1} = R - P(QU_i + CE_{i+1}) \tag{27}$$

where P denotes the plant transfer function and

$$E_{i+1}(1+PC) = R - PQU_i = (1 - Q)R - PQU_i + QE_i + PQU_i \tag{28}$$

Being $S := 1/(1+PC)$ the sensitivity function, the last equation can be written as,

$$E_{i+1} = S(1 - Q)R + SQE_i \tag{29}$$

According to latter equation, it is possible to write

$$(R - Y_{i+1}) = S(1 - Q)R + SQ(R - Y_i) \tag{30}$$

and being $Y_{i+1} = PU_{i+1}$, the last equation can be rewritten as

$$PU_{i+1} = R - S(1 - Q)R - SQR + SQPU_i = TR + SQPU_i \tag{31}$$

where $T := 1 - S$ is denoted as complementary sensitivity function. In consequence,

1 In this paper variables in time domain are denoted with small letters and variables in s-domain are denoted with capital letters.

$$U_{i+1} = \frac{T}{P} R + SQU_i \tag{32}$$

Also, based on [23], the following remark for LTI system without model uncertainty can be enunciated:

Remark 1. *Consider a feedback-based ILC scheme in Fig. 2 with the updating formula (25) and the plant is a LTI system without model uncertainty. If there exists C(s) such that the nominal stability is satisfied, then by adopting Q such that* $||SQ||_\infty \le 1$ *the tracking error is reduced as i is increased and it is bounded for all* $i \in Z^+$ *and converges uniformly to*

$$e_i(t) = \lim_{i\to\infty} e_i(t) = L^{-1}\left(\frac{S(1-Q)}{1-SQ} R\right) \tag{33}$$

when $i \to \infty$ *in the sense of the* l_2*-norm.*

Proof It is easy to proff this remark for nominal stability following similar steps to authors mentioned above [23].
By similar reasoning and according to (32) and taking into account that $\lim_{i\to\infty} U_{i+1}(s) = \lim_{i\to\infty} U_i(s) = U_\infty$,

$$U_\infty(t) = \frac{T}{P} R + SQU_\infty \tag{34}$$

or

$$U_\infty(t) = \frac{T}{P(1-SQ)} R \tag{35}$$

Based on $E_\infty = S(1 - Q)/(1 - SQ)$ R and (35) the following remark can be enunciated:
Remark 2. *Consider the feedback-based ILC scheme in Fig. 2 with the updating formula (22) and the plant is a LTI system without model uncertainty. If there exists C(s) such that the nominal stability is satisfied, then by adopting* $Q = 1$ *the perfect control can be reached as* $i \to \infty$.
Proff According to (29) then $E_\infty = S(1 - Q)R + SQE_\infty$. Thus, from (34) note that, if $Q = 1$, then $E_\infty = 0$ and $U_\infty = (1/P)R$, and in consequence $Y_\infty = R$.

4.4. Adaptive PI Feedback Based-ILC

Based on the last remarks the following design procedure is enunciated:
Design Procedure 2 (Nominal Case):

- Step 1. Estimate the PI controller parameters according to Procedure 1 such that the nominal stability, the performance and the restriction are satisfied.
- Step 2. Set $Q = 1$ or well $Q(s)$ to be low pass filter such that, $|Q(\omega)| \to 1\ \forall\ \omega \in [0, \omega_c]$, and $|Q(\omega)| \to 0\ \forall\ \omega > \omega_c$ with ω_c a cut-off frequency.
- Step 3. Use the ILC updating formula (19) or (25).
- Step 4. Compute the control signal u_i.
- Step 5. If $t = T_f$, where T_f is the fixed interval time for every iteration, stop the procedure; otherwise, go to Step 1.

5. NUMERICAL SIMULATION

In this section, the non-linear batch reactor control with strong parametric uncertainty is studied by means of numeric simulation using adaptive feedback based-ILC presented in previous section.

As it was remarked above, every batch reactor has an operation sequence which consists of three stages, start-up, run and shutdown. Assuming that, the controlled temperature inside the reactor is monitored during these three stages and, the adaptive feedback based-ILC scheme was implemented by means of the combination of the design procedures 1 and 2. Furthermore, an additional hypothesis related to the batch reactor behaviour has been added. Here, it is considered that the chemical reaction begins when the temperature inside the reactor is equal 30°C. This consideration makes more attractive the physical system here studied.

5.1. Example 1. Without constrain in the manipulated variable

Firstly, let it considers the batch reactor presented in the Section 2 where the manipulated variable (cooling jacket temperature) can change without saturation and, a feedback-bases ILC without adaptive scheme is implemented, that is the PI controller has fixed parameters calculated with an initial identification.

Figure 3 shows l_2-norm[2] ratio between dynamic error and the maximum l_2-norm of the dynamic error obtained when the traditional feedback is implemented alone, that is when $i = 0$ ($\| e \|_{2,0}$). Clearly, the $\| e \|_{2,i}$ is reduced as k is incremented, and in consequence, the convergence of the error is monotonic and the definitions 1, 2 and 3 could be reached.

Clearly, when there are no limits for the manipulated variable, the adaptive scheme is not necessary because of the feedback-based ILC with fixed parameter has the capacity to control the system in spite of non-linearities.

Notice that, $\|e\|_{2,i}$ is approximately reduced in a more than 80% for $i = 10$ with respect to $\| e \|_{2,0}$. In addition, the l_2-norm could be further reduced because the manipulated variable can change without saturation.

Figure 4 compares the performance obtained with the traditional feedback ($i = 0$) and tenth iteration for the feedback-based ILC with PI with fixed parameter. Notice that, i) when the feedback-based ILC is implemented during the start-up and the shutdown, the ramp tracking error is very small; ii) the overshoot produced during the reaction starting time is reduced because of the unbounded manipulated variable and in consequence, the system has an unbounded capacity to extract energy; therefore, iii) l_2-norm of the error is considerably reduced with only 10 iterations.

[2] The l_2-norm refers to the Euclidean norm defined in the traditional form.

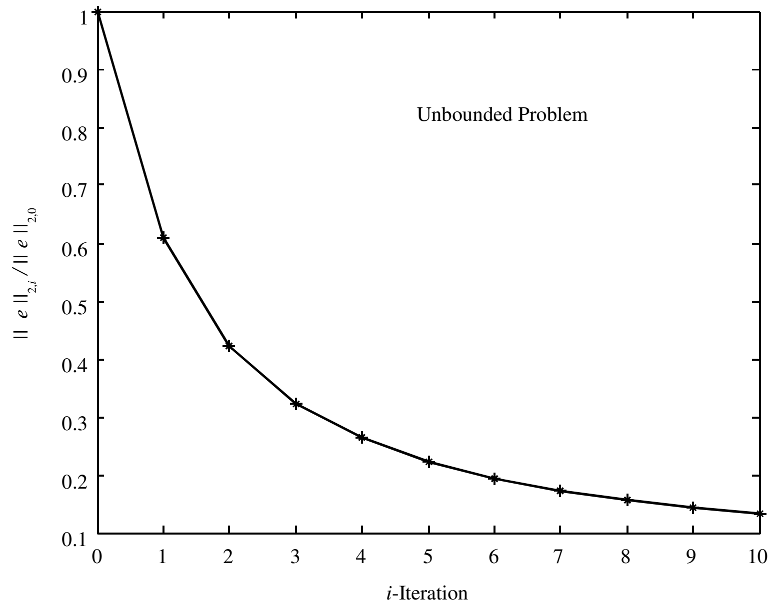

Figure 3. Ratio between $\| e \|_{2,i}$ and $\| e \|_{2,0}$ vs. i-trail when the feedback-base ILC is implemented with an unbounded manipulated variable.

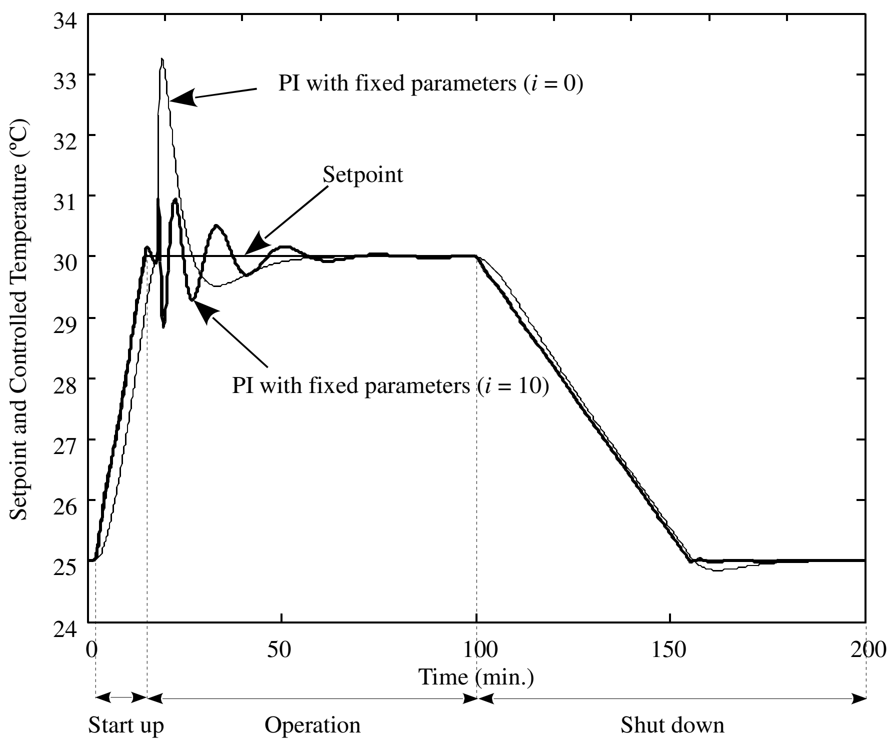

Figure 4. Setpoint and controlled temperature for iteration 0 (traditional feedback) and 10 when the manipulated variable is unbounded.

5.2. Example 2. With constrain in the manipulated variable

Now, let it considers the same batch reactor of the previous section but now the manipulated variable is bounded between the maximum and minimum specified in Section 2.
Figure 5 compares the performance obtained with the traditional feedback (i = 0) and tenth iteration for the feedback-based ILC when there are constrains in the manipulated variable. For this case, the reader can notice that the performance is not considerably improved in spite of the control system had 10 iterations to learn.

Figure 6 shows the controlled temperature performance obtained by a traditional PI feedback and it is compared with the one obtained by means of adaptive PI feedback-based ILC implementation according to Section 4.4. It is possible to distinguish that the controlled temperature can follow the reference with a acceptable exactitude when the adaptive feedback based-ILC is implemented. Furthermore, the reader can note that there is not strong difference as i is increased.

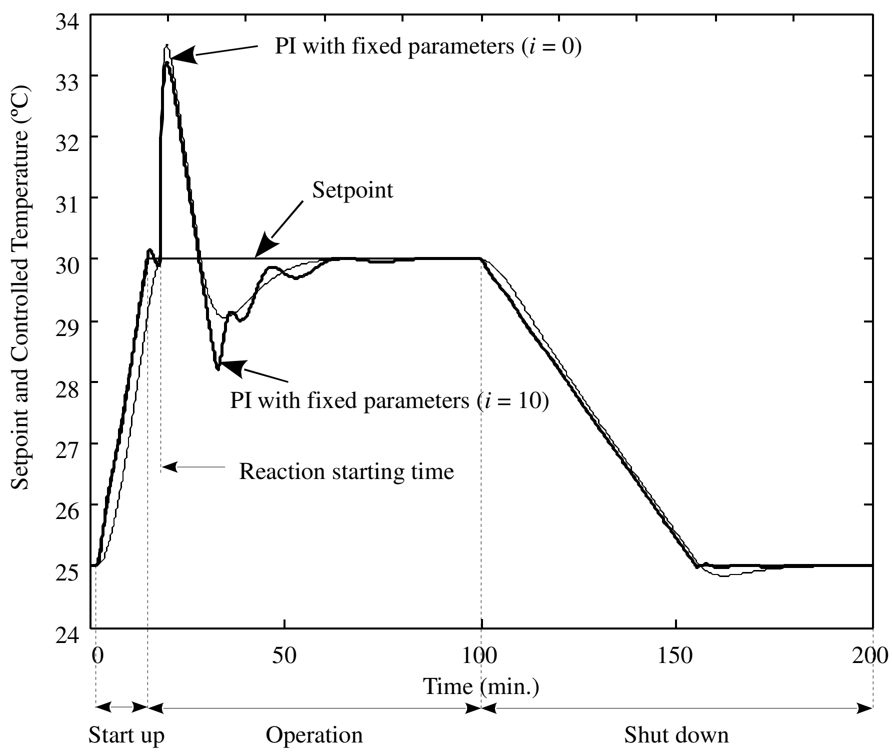

Figure 5. Setpoint and controlled temperature for iteration 0 (traditional feedback) and 10 (Feedback-based ILC) with limit in the manipulated variable.

Figure 7 shows the dynamic errors obtained with the three cases presented in the Fig. 6. Clearly, the dynamic error is considerably smaller when the adaptive feedback based-ILC is implemented.

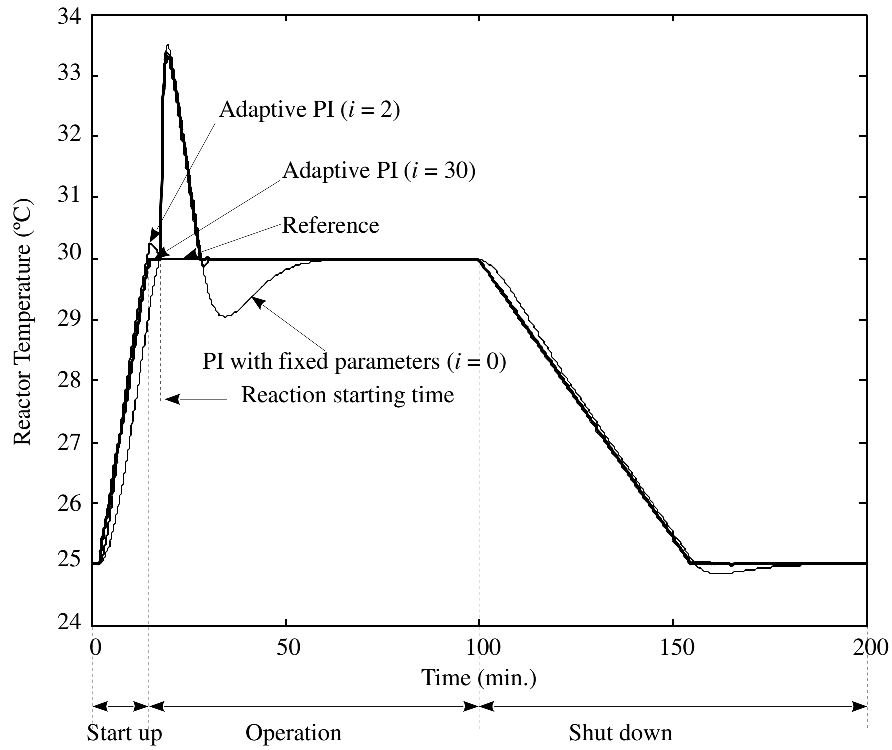

Figure 6. Controlled temperature inside the batch reactor when traditional feedback and adaptive feedback based-ILC are implemented.

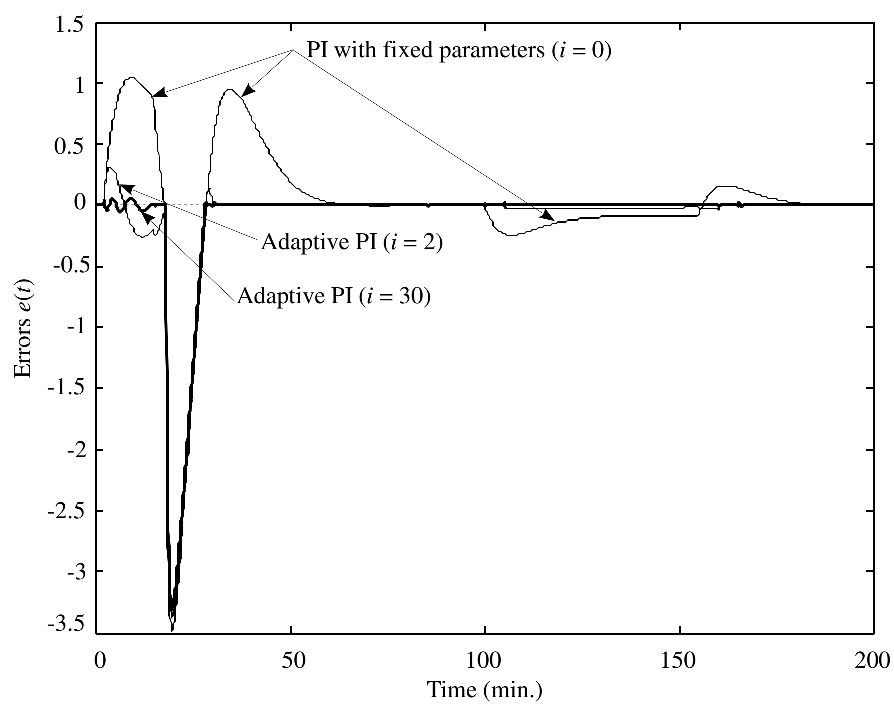

Figure 7. Dynamic errors for the cases studied in Fig. 6.

From a practical point of view, the error is practically zero in almost all the time interval, excepting a small interval associated to the reaction starting time. Neither the traditional feedback control nor the adaptive feedback based-ILC can reject that disturbance due to the saturation of the manipulated variable. This phenomenon is showed in Fig. 8. Notice that when the reaction begins both control schemes try to correct the increase of temperature in the reactor, but quickly the manipulated variable is saturated and as consequence, the peak of temperature observed cannot be avoided. On the other hand, outside of the time interval of the manipulated variable saturation, the correction of adaptive feedback based-ILC is better than the traditional feedback due to the control system is learning.

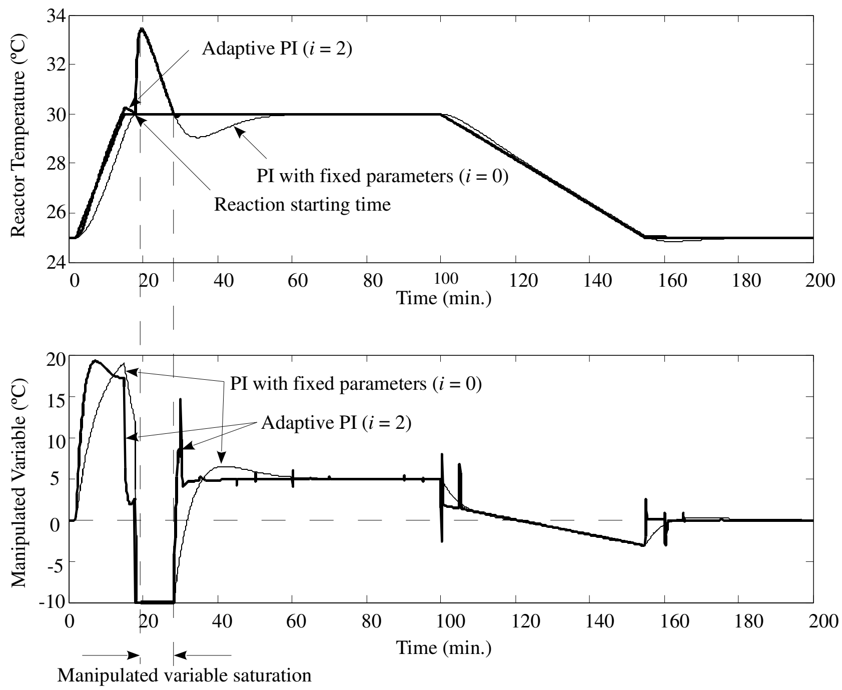

Figure 8. Temperature reaction response and manipulated variable for the traditional feedback and adaptive feedback based-ILC during the second iteration.

Figure 9 compares the l_2-norm ratio between dynamic errors obtained with the ILC schemes and the traditional feedback as a function of the iteration index i. Here, two ILC schemes were used, one of them was a feedback based-ILC implemented with PI controller with fixed parameter and, the other one was a feedback based-ILC implemented with an adaptive PI controller according to Section 3.1. Here $\| e \|_{2,i}$ denotes the l_2-norm of the error obtained with the i-iteration while, $\| e \|_{2,0}$ denotes the of the error obtained with the traditional feedback with PI controller with fixed parameter.

Notice that, the feedback based-ILC scheme with fixed parameter PI controller does not have a monotonic convergence of the $\| e \|_2$ and the Defns. 1, 2 and 3 are not satisfied. In other words, the equilibrium signal is not stable for this case but, this fact does not imply that the control system is unstable during the batch operation. On the contrary, when the adaptive feedback based-ILC is implemented an almost monotonic convergence of the $\| e \|_2$ is reached. Only in few points, the requirement $\| e_{i+1} \|_2 \leq \| e_i \|_2 \ \forall \ i \geq 0$ is not fulfilled but, a decreasing error is reached in almost every iteration. Clearly, Fig. 6 is showing an improvement in the performance because of adaptive scheme introduced. Certainly, if the designer wants a monotonic convergence of the $\| e_i \|_2$, an optimal learning algorithm should be introduced as it is suggested by [1], [2] and [18]. But, this last objective is not pretended in this work. Without doubt, if the optimal learning algorithm had been implemented, the behaviour that shown in Fig. 8 could not have been manifested.

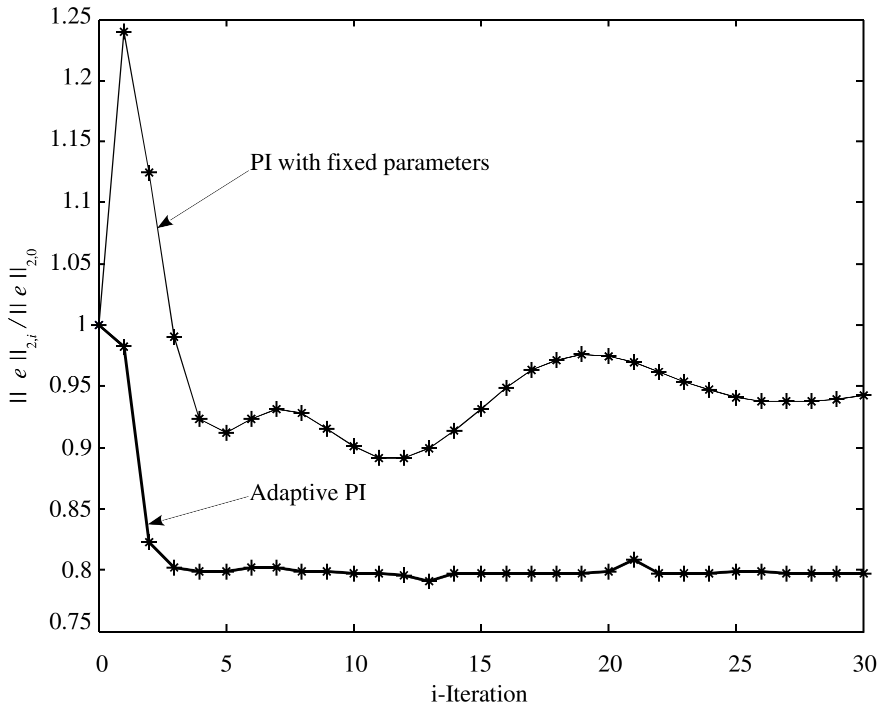

Figure 9. Ratio between $\| e \|_{2,i}$ and $\| e \|_{2,0}$. Notice that, $\| e \|_{2,i}$ is approximately reduced in a 20% for $i \geq 3$ with respect to $\| e \|_{2,0}$. In addition, the l_2-norm could not be further reduced because of the saturation of the manipulated variable.

Finally, notice that the tracking equilibrium error does not indeed tend to zero as $i \to \infty$ and, it is associated to manipulated variable saturation during a small time interval. However, the only way to extract the maximum possible energy is saturating the manipulated variable (at least for a period of time), achieving maximum benefit in terms of energy. In other words, implementing an optimal learning algorithm and allowing the saturation of the manipulated variable, the monotonic convergence of the error (Defn. 1) could have been reached but, the batch reactor never will reach $\| e_\infty \|_2 = 0$ (Defn. 3) because the system has bounded capability to extract energy. In addition, the reader may note that the maximum possible performance and the equilibrium signal are next to being achieved with a few iterations.

6. CONCLUSIONS

In this work firstly, it is important to remark that without the necessity of considering a robust design, the adaptive PI feedback-based ILC was justified by means of using a nominal model which is identified on line. Furthermore, the adaptive capacity of the control strategy is reached because the linear model is updated at each sampling time.

Secondly, it was presented a minimal review of ILC theory and it was possible to extend theoretical results obtained by [23] for the feedback-based ILC by introducing the Rems. 1 and 2 for a nominal case.

Based on the results from different numeric simulations, it is possible to conclude that the control system can reach the maximum possible performance (in practical terms) with a few iterations when the adaptive feedback-based ILC is implemented in this reactor. On the contrary, if the feedback-based ILC is implemented alone, a stable equilibrium signal with a monotonic terminal convergence will be little probable, especially if the non-linearities of the system are considerably strong.

The methodology of combining the STR scheme with feedback-based ILC has showed to be an attractive alternative for chemical engineering problems with good results.

ACKNOWLEDGEMENTS

The author would like to the Universidad Nacional del Litoral for the financial support received.

REFERENCES

[1] Amann, N. (1996) *Optimal Algorithms for Iterative Learning Control*. Ph.D. Thesis, University of Exter.

[2] Amann, N., D. H. Owens & E. Rogers, (1996) "Iterative Learning Control for Discrete-Time Systems with Experimental rate of convergence", *IEE Proc.-Control Theory Appl.*, Vol. 143, No. 2, 217-224.

[3] Arimoto S., S. Kawamura & F. Miyazaki, (1984) "Bettering Operation of Robots by Learning", *Journal of Robotic System*, Vol. 1, No. 2, pp123-140.

[4] Astrom K. J. & B. W. Wittenmark (1989) *Adaptive Control*, Addison – Whesley.

[5] Bien Z. & J-X Xu. , (1998) *Iterative Learning Control: Analysis, Design, Iteration and Application.* Kluwer Academic Publishers.

[6] Chen Y. & C. Wen, (1999) *Iterative Learning Control.* Springer Verlag.

[7] Chien C. J. & C.-Y. Yao, (2004) "An Output-Based Adaptive Iterative Learning Controller for High Relative Degree Uncertain Linear System", *Automatica*, Vol. 40, pp145-153.

[8] Cueli J. R. & C. Bordons (2008) "Iterative nonlinear model predictive control.stability, robustness and applications", *Control Engineering Practice,* Vol. 16, pp1023-1034.

[9] Horowitz R., "Learning Control of Robot Manipulators", (1993) *Journal of Dynamic Systems, Measurement and Control*, Vol. 115, pp402-411.

[10] Kurek J. E. & M. B. Zaremba, (1993) "Iterative Learning Control Synthesis Based on 2-D System Theory", *IEEE Trans. Automat. Contr.*, Vol. 38, No. 1, pp121-125.

[11] Lee, J. H. & K. S. Lee., (2007) "Iterative learning control applied to batch processes". *Control Engineering Practice*, Vol. 15, pp1306-1318.

[12] Lee K. S., I.-S. Chin, H. J. Lee & J. H. Lee, (1999) "Model Predictive Control Technique combined with Iterative Learning for Batch Processes", *AIChE Journal*, Vol. 45, No. 10, pp2175-2187.

[13] Lee K. S. & J. H. Lee, (1997) "Model Predictive Control for Nonlinear Batch Processes with Asymptotically Perfect Tracking", *Computers Chem. Engng.*, Vol. 21, *Suppl.*,S873-S879.

[14] Lee, K. S. & J. H. Lee, (2003) "Iterative learning control-based batch processes control technique for integrated control of end product properties and transient profiles of process variables". *Journal of Process Control*, Vol. 13, pp607-621.

[15] Moon J. H., T. Y. Doh & M. J. Chung, (1992) "A Robust Approach to Iterative Learning Control Design for Uncertain System", *Automatica*, Vol. 34, No. 8, pp1001-1004.

[16] Norrlöf M. *Iterative Learning Control. Analysis, design, and experiments.* Ph. D. Thesis, Linköpings Universtet, Sweden, (2000).

[17] Ogata, K. (2009) *Modern Control Engineering*. Prentice Hall, 5th edition.

[18] Owens D. H. & Hätönen J., (2005) "Iterative Learning Control – An Optimization Paradigm", *Annual Reviews in Control*, Vol. 29, Issue 1, pp57-70.

[19] De Roover. D. (1996) "Synthesis of a robust iterative learning control using an hinf approach". In Proc. *35th Conf. Decision Control*, pp3044-3049, Kobe, Japan.

[20] Sontag, E. D. (1998) *Mathematical Control Theory. Deterministic Finite Dimensional System.* Springer - Verlag.

[21] Doh T. Y., J. H. Moon, K. B. Jin & M. J. Chung, (1999) "Robust ILC with Current Feedback for Uncertain Linear System", *Int. J. Syst. Sci*, Vol. 30, No. 1, pp39-47.
[22] Tayebi A., (2004) "Adaptive Iterative Learning Control for Robot Manipulators", *Automatica*, Vol. 40, pp1195-1203.
[23] Tayebi A. & M. B. Zaremba, (2003) "Robust Iterative Learning Control Design is Straightforward for Uncertain LTI System Satisfying the Robust Performance Condition", *IEEE Trans. Automat. Contr.*, Vol. 48, No. 1, pp101-106.
[24] Uchiyama, M. (1978) "Formulation of high-speed motion pattern of a mechanical arm by trail". *Trans. SICE*, Vol. 6, pp706-712.

Authors

He was born in Argentina and he received his PhD degrees at National University of Litoral in 1996. Then, did a postdoctoral residence at University of Florida during 1999-2000. He is involved in academic and research activities in areas such as control system theory, robust and predictive control and fault diagnosis.