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Adaptive System Control with PID Neural Networks

F. Shahraki[a], M.A. Fanaei[b], A.R. Arjomandzadeh[a]
[a]Department of Chemical Engineering, University of Sistan and Baluchestan, Zahedan, Iran.
[b]Department of Chemical Engineering, University of Ferdowsi, Mashhad, Iran.

In this paper, PID neural network, which is an adaptive controller, has analyzed and compared with two other conventional PID algorithms through computer simulation and experimental study. Cancellation and pole placement are the two selected conventional algorithms. In the simulation study, the effects of factors such as non-minimum phase behavior and model changes on the performance of schemes are investigated. In the experimental study, performance of controllers on pressure control of two serial tanks is investigated. Simulation and experimental results demonstrate that PID neural network can be tuned easily and has better performance in compare with two conventional schemes especially in the case of non-minimum phase behavior and model mismatch. However, it has slower dynamic in compare with cancellation algorithm.

Introduction

PID controller is the most common control algorithm is used widely in chemical process as could be seen in Desbourough et al. (2002) and also Astrom et al. (2001). This is because of its good performance as long as a simple structure, in the case that it tunes well. By now, a lot of tuning schemes have been devised such as Atherton et al. (1999) Martins et al. (2000) but performance of this controller degrades during the time due to process non linearity or process time varying parameters, so it must be retuned. Retuning such a controller being performed through a trial and error procedure which is a time consuming task and requires a skillful operator. In an adaptive PID, controller parameters automatically and continuously tuned in accordance with changes of the process parameter so as explained in Widrow et al. (1985) it could be a solution to this problem. In recent years, artificial neural networks have been progressed a lot. Their ability to estimate every nonlinear function with at least one hidden layer with sufficient neurons has been proved as reported in Hornic et al. (1989). These models are data driven and extensively used in simulation and control of nonlinear process such as works done by Hecht (1989) and Tsen et al. (1996). So in works like Martins et al. (2000), Junghui et al. (2004), Andrasik et al. (2004), designers try to use neural networks to modify PID controllers. Furthermore, simplicity is one of the important features of PID controllers so designers try to keep this characteristic. In schemes suggested by Widrow et al. (1985) and Junghui et al. (2004) with no major changes in conventional PID structure, try to use capability of neural networks. The first scheme uses prediction capability of neural networks and the second one for tackling sever

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nonlinearity of process. PID neural network (PIDNN) which is proposed by Huaillin et al. (2000) is a new kind of networks and its hidden layer neurons simply work as PID controller terms through their activation functions thus it simultaneously utilizes advantages of both PID controller and neural structure. In this paper, performance of this direct controller which performs an adaptive control through online learning process has been studied and compared with two other conventional adaptive PID controllers. In the rest of the paper, after brief review of selected schemes, their performance analyzed and compared through computer simulation and then by experimental study and finally conclusion is given.

Compared Schemes Structures

PID neural network

As it is shown in figure 1, this controller has a simple feed forward neural network which consists of 2-3-1 structure, so it has three layers.

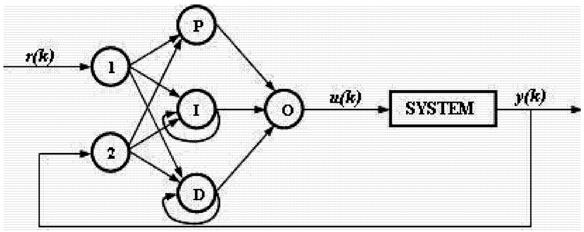


Figure 1. Structure of PIDNN

There are two proportional neurons in input layer with following activation function. One for receiving system setting and other for receiving process output.

$$O_i(k) = \begin{cases} 1 & net_i(k) > 1 \\ net_i(k) & -1 \le net_i(k) \le 1 \\ -1 & net_i(k) < -1 \end{cases} \tag{1}$$

In the hidden layer three neuron of different type of proportional, integral and derivative neuron exist. The activation function for integral neuron is as followed.

$$O_j(k) = \begin{cases} 1 & O_j(k) > 1 \\ O_j(k-1) + net_j(k) & -1 \le O_j(k) \le 1 \\ -1 & O_j(k) < -1 \end{cases} \tag{2}$$

and the activation function for derivative neuron is as followed.

$$O_j(k) = \begin{cases} 1 & O_j(k) > 1 \\ net_j(k) - net_j(k-1) & -1 \le O_j(k) \le -1 \\ -1 & O_j(k) < -1 \end{cases} \tag{3}$$

In the hidden layer, the neurons inputs are

$$net_i = \sum_{j=1}^{2} w_{ij} O_j \tag{4}$$

Table 1. Design parameter for different schemes

Scheme	Design parameter
PIDNN	α (learning rate)
Cancellation	ϕ_m (phase margin)
Pole placement	p (desired pole location)

Where i is the number of neuron in hidden layer and j is the number of neuron in input layer. Finally hidden layer is comprised of one proportional neuron which produces controller output while its neuron input is

$$net_o = \sum_{j=1}^{3} w_{oj}\ O_j \tag{5}$$

Where j is the number of neuron in hidden layer and o is the output layer's single neuron. Learning of this network is done through online back-propagation algorithm. Objective function for this algorithm is as follow and the aim of the PIDNN is to minimize this objective function.

$$J = \frac{1}{N}\sum_{k=1}^{N} [r(k) - y(k)]^{2} \tag{6}$$

Where N is the total number of sampling intervals.

Conventional schemes

By now, several schemes for adaptive tuning of PID controller have been proposed as reported in Astrom et al. (1988). Shahrokhi et al. (2000) compared four adaptive schemes for tuning of PID controller. With regard to the result of this work, two schemes among them named as cancellation by Banyacz (1985) and pole placement by Tjorkro (1985) have been analyzed as a conventional schemes in this study. In the first scheme, the process dynamic is modeled with a second order model and the controller parameters are designed to cancel the process model poles and achieve the desired phase–margin. In the second scheme, the process model poles are cancelled, however the controller gain is adjustment to place the closed loop pole at the desired location. These two models are indirect controller, so they need an algorithm for identification of the process parameter. For this purpose a recursive least square (RLS) with variable forget factor and proposed by Fortescue et al. (1981) has been used.

Computer Simulation Results

In this section, the performance of the three mentioned algorithm investigated through computer simulation. Effects of process model change and non-minimum phase behavior are investigated. There is one design factor in accordance with table (1) for each algorithm. The values of these parameters are so selected to minimize the sum of absolute error (IAE) as follow.

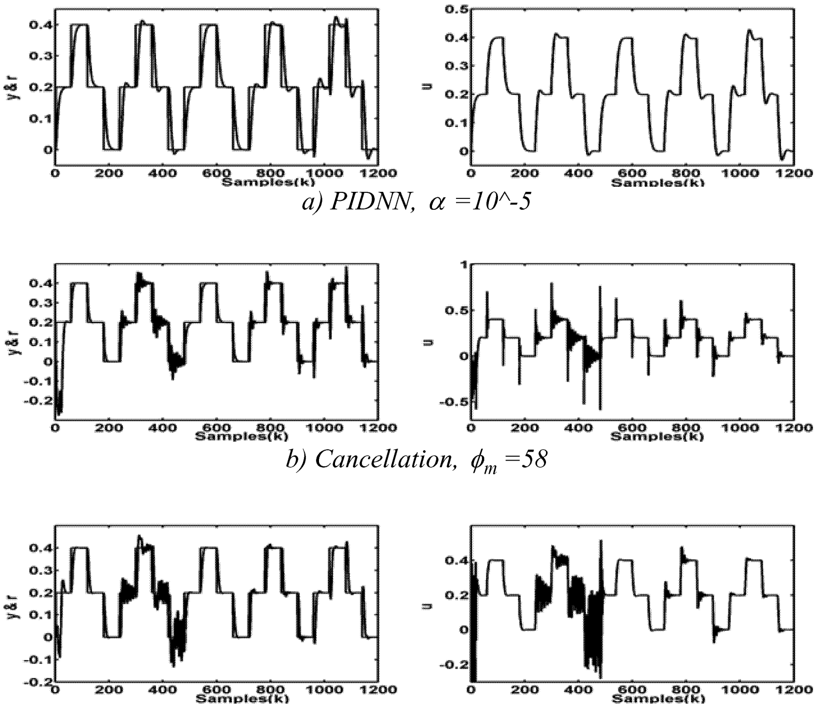
$$IAE = \int \left| e(t) \right| .dt \tag{7}$$

The sequence of model changes and their corresponding time intervals are given in table (2). The first two models are of second order with different delay time and the following two models are of first order with different delay time. The fifth model is a non-

Table 2. Simulated process model (sampling period is 3 seconds).

Sequence of apply	Samples	Continuous model
1	0-240	$\frac{1}{1+10s+40s^2}$
2	240-480	$\frac{e^{-3s}}{1+10s+40s^2}$
3	480-720	$\frac{1}{1+10s}$
4	720-960	$\frac{e^{-3s}}{1+10s}$
5	960-1200	$\frac{(0.5-s)e^{-s}}{(3s+1)(3.53s+1)}$

minimum phase model. The simulation results are illustrated in figure (2). As can be seen, PIDNN has much more better response in compare with two conventional schemes and this is owing to the fact that it has a neural network structure and has more robust performance as explained in Schalkoff (1997). Additionally, it needs less trial and error procedure to be tuned.



a) PIDNN, α =10^-5

b) Cancellation, ϕ_m =58

c) Pole placement, p =0.6

Figure 2. Closed loop response

Experimental Results

As a result of simulation study none of two conventional schemes act better than PIDNN. Therefore in the experimental study, PIDNN is only compared with cancellation scheme. Process arrangement could be seen in figure (3). In this process, the second tank pressure y(k) is controlled by input air flow rate to the first tank u(k).

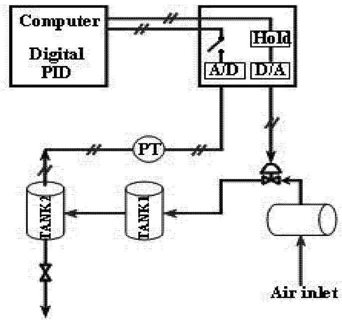
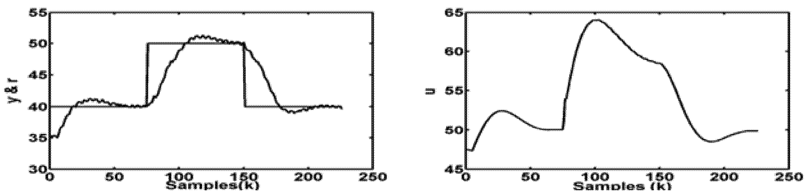


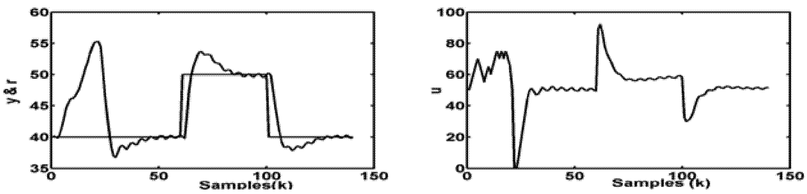
Figure 3. Experimental set up

If RLS does not make good estimation of process model cancellation scheme performance degrade so in the beginning of the process some Pseudo Random Binary Sequence (PRBS) in the form of open loop for 20 sampling interval is applied to the algorithm to help RLS to estimate process model.

As it is shown in figure (4), both schemes have satisfactory response but PIDNN has better performance especially in the beginning of the control session. That is owing to the fact that RLS algorithm in cancellation schemes does not make good estimations of process parameters despite of applying PRBS. Furthermore cancellation scheme has larger overshoots in compare with PIDNN response although in the following steps it gets better and PIDNN shows slower response. This is because of its training algorithm which is in the form of back propagation with fix learning rate.



a) PIDNN, α =10^-5



b) Cancellation, ϕ_m =70

Figure 4. Experimental response

Conclusion

In this paper, PIDNN has compared with two conventional schemes. Results show PIDNN has better performance in compare with cancellation and pole placement algorithm in the case of model mismatch and also processes with non-minimum phase behavior. PIDNN requires less trial and error for tuning and has more robust performance. But it has slower dynamic in compare with cancellation algorithm.

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