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Neural Network Self-Tuning Control Of Hot-Spot Temperature In A Fixed-Bed Catalytic Reactor

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ABSTRACT

This paper demonstrates the possibility of applying artificial neural networks (ANNs) in the self-tuning PID control of the hot-spot-temperature in a fixed-bed catalytic reactor system. In this reactor system sulfur dioxide is oxidized using vanadium pentoxide catalyst. Unlike the conventional self-tuning PID control algorithm, the ANN applied to the self-tuning PID (NNW-PID) philosophy is an inherent nonlinear estimator and therefore identifies a nonlinear system directly from historical data supplied by the plant. In the majority of control applications, the ANN is employed as a predictor of future outputs within an established predictive control algorithm [1,2]. In this paper we propose a scheme where an ANN is employed on-line with a non predictive PID controller to give adaptive control of the reactor. This is accomplished by applying the values of the ANN weights, that are continually updated by the algorithm, to give the relevant PID controller parameters. Since real plant data is used to train the network, the algorithm can be applied to similar real-world problems.

1 Introduction

Artificial Neural Networks [3] are a technology from which computers can learn [4] directly from the data presented to them in order to perform classification, function estimation and other similar tasks [5]. ANNs are gaining increasing acceptance as a replacement for statistical and other modeling techniques. ANNs, sometimes described as ‘a solution in search of a problem’, have been applied to diverse problems that include financial forecasting, robot control, image processing, and control of chemical plants [6]. In this application an ANN is used to form an electronic representation or model of a fixed-bed catalytic reactor system by a process of learning from the reactor's historical data. The reactor is used in the production of sulfur trioxide by oxidation of sulfur dioxide using vanadium pentoxide catalyst. The oxidation of sulfur dioxide on vanadium pentoxide catalyst is an exothermic reaction which at temperatures above 670K gives rise to a temperature peak (hot-spot) in the catalyst bed. The activity of the catalyst is time varying and so are the dynamics of the hot-spot which gives rise to a complex control problem requiring control strategies capable of tracking these changes as they occur. In this paper we suggest the use of an ANN model within a non predictive scheme to recommend PID controller parameters. This paper is organized as follows: a brief introduction to ANNs and applications in process control. This is followed by a description of the proposed control algorithm, then the results and conclusions.

2 A Brief Review of Application Of Artificial Neural Networks

The history of ANNs cover names like Hebb (1949), Rosenblatt (1962), Minsky and Paper-t (1969) and Rummelhart and McClelland and Pao (1989). The paper by Widrow et *al* [7] gives the history of ANNs over thirty years and introduces the various network types. Keeler [8] summarizes the features of ANNs that make them attractive for utilization of historical data as follows:

> *Neural nets are nonlinear regression algorithms that can model high dimensional systems and have a very simple user interface; they work well with both batch and continuous processes, and they can be used in either static or dynamic modeling.*

The design of control systems involves the steps of [9]: constructing a mathematical model describing the dynamics of the plant to be controlled; application of mathematical techniques to this model to derive a control law. In practice, the exact representative model of the plant is difficult to obtain, more so for nonlinear systems. ANNs are attractive to model chemical processes, an area with two major concerns of increasingly complex systems, and the need to accomplish increasingly demanding design requirements with less precise knowledge of the plant and its environment. ANNs are the answer since they "*need history, which is often abundant, and not theory, which is often absent*"[5].

Modeling with ANNs is radically different from the traditional first principles modeling approaches based on our understanding of chemistry and physics. As Donne and Ozguner [10] point out, a large percentage of knowledge is devoted to linear systems with little attention to nonlinear systems. For nonlinear systems restrictive assumptions (on the nature of the nonlinearity or differential equation) are made to keep the mathematics manageable. It takes many person-years to develop an adequate model. Further, the application of such a model is severely constrained by its limited fidelity, making it brittle for some real world problems. The difficulties arise because many processes exhibit: nonlinearity, high dimensionality, inherent time-delays, noisy environment, unmeasured and uncontrolled change [8].

The growing preference for batch and semi-batch processes in production of special chemical products with a good return means that the understanding of reactor dynamics often at a considerable cost and time is not justifiable for such processes. ANNs with their known advantages [8,9,11,12] over first principles and statistical modeling will continue to be seen as a natural tool in the development of models for control to meet challenges such as improved efficiency, productivity as well as to comply to tighter environmental controls [13,141. Montague *et al.* [15] indicate that potential means to enhance control performance is to incorporate predictive models within control schemes of which Narendra and Parthasarathy [16] suggest several configurations.

The benefits of applying ANNs in process control have been presented by several authors [5,8,11]. The ANN learns the process dynamics from the historical process data, in effect capturing the fully nonlinear, high dimensional response surface of the process. It has been shown [17] that ANNs can approximate any arbitrary function by using simple functions (typically sigmoidal) by combining them in a multilayer nested structure. Backpropagation [18] is a popular network used to demonstrate this capability. For this problem we have used a three layered architecture of the backpropagation network.

3 The Generalized Delta Rule

The backpropagation algorithm presented uses the delta rule [2]. Here the total input to a neuron **j** is the product of the weighted sum of the outputs (activations) from each of the connected neurons **a,,** and their respective weights ω_{hj} plus a bias or offset term θ_j [Fig. 1], viz.:

$$h_j = \sum_h \omega_{h,j} a_h + \theta_j \tag{1}$$

where

$$a_h = f(h,j) = \frac{1}{1+e^h} \tag{2}$$

The error signal of an output unit derived on the basis of the sigmoid activation function defined in equation (2) is:

$$\delta_j = (a_j^d - a_j) a_j (1 - a_j) \tag{3}$$

where a^d is the desired output and a_j is the actual process output. The weight adjustments , $\Delta\omega_{h,j}$, in the output layer associated with the **j**th output are given by:

$$\omega_{h\ j} = \gamma\delta_j a_h \tag{4}$$

where y is the learning rate. Smaller values of y produce more accurate weight convergence but at the cost of reduced learning speed. Faster learning speeds can be achieved by modifying equation (4) to incorporate a *momentum* term a thus:

$$\Delta\omega_{h,j} = \gamma\delta_j a_h (1 - a) + \alpha\Delta\omega_{h,j} \tag{5}$$

The momentum term decreases the sensitivity of the backpropagation network to small variations in the error surface, thereby allowing the network to avoid being confined within shallow local minima. Such an eventuality would prevent the network from further reducing the output error. The error for the **h**th hidden layer node is:

$$\delta_h = a_h (1 - a_h) \sum \delta_j \omega_{h,j} \tag{6}$$

and the weights in the hidden layer are updated by using:

$$\Delta\omega_{i,h} = \gamma a_i \delta_h (1 - a) + \alpha\Delta\omega_{i,h} \tag{7}$$

It is noted that an optimum number of nodes in the hidden layer are required in order to adequately learn the process dynamics, a figure which is found experimentally.

4 The Neural Network Self-tuning Algorithm

Consider a process represented by a discrete-time Carma model of the form [19,20]:

$$A(z^{-1})y(t) = z^{-k} B(z^{-1})u(t) + c(z^{-1})\xi(t) \tag{8}$$

where $A(z^{-1}) = 1 + \alpha_1 z^{-1} + a_2 z^{-2} + \ldots + \alpha_{n\alpha} z^{-n\alpha}$

$$B(z^{-1}) = \beta_0 + \beta_1 z^{-1} + \beta_2 z^{-2} + \ldots + \beta_{n\beta} z^{-n\beta} \tag{9}$$

$na = 2$, $n\beta = 0$ are the orders of the A and B polynomials.

The general structure of the self-tuning PID (STPID) algorithm is given by:

$$R(z^{-1})u(t) = S(z^{-1})[w(t) - y(t)] \qquad (10)$$

where R is the differencing factor (i.e. $R = 1 - z^{-1} = Au$) and w(t) is the reference set point. S is the error filtering polynomial of the form:

$$S(z^{-1}) = s_0 + s_1 z^{-1} + s_2 z^{-1} + \ldots\ldots \qquad (11)$$

Taking S to be second order, and ε (t) = w(t) - y(t) equation (10) becomes:

$$\Delta u(t) = s_0 \varepsilon(t) + s_1 \varepsilon(t-1) + s_2 \varepsilon(t-2) \qquad (12)$$

Substituting equation (10) into equation (8) yields the closed-loop equation:

$$y(t) = \frac{z^{-1}BS}{AR + z^{-1}BS} w(t) + \frac{CR}{AR + z^{-1}BS} \xi(t) \qquad (13)$$

The pole-placement approach implies the movement of the closed-loop poles of the characteristic equation in (12) from their open loop locations to prescribed values given by a preset tailoring polynomial $\Gamma = 1 + \tau_1 z^{-1} + \tau_2 z^{-2} + \ldots\ldots$ and for the NNW-PID control strategy the following pole placement algorithm is used:

$$AR - z^{-k}BS = \Gamma \qquad (14)$$

The polynomial Γ is chosen to be of order corresponding to the desired controlled response. The roots of this polynomial are set to within the unit circle in the z-domain for stable control. In this work a first order polynomial was found to be adequate.

For a single hidden-layered neural network with an input/output structure made up of past outputs and past inputs, by employing the relationships for the backpropagation learning rule we may write for the past outputs:

$$\alpha_i = (-1) \sum_{h=1}^{P} \omega_{h,j} \omega_{i,h} \qquad (15)$$

and for past inputs:

$$\beta i = \sum_{h=1}^{P} \omega_{h,j} \omega_{i,h} \qquad (16)$$

where $\omega_{i,h}$ and $\omega_{h,j}$ are the weights associated with the neurons of the hidden and output layers respectively, i being the i^{th} input node, whilst P is the number of output layer nodes.

The S polynomial coefficients for a pole-placement design are evaluated using the following relationships:

$$
\begin{aligned}
s_0 &= (\tau_1 - \alpha_1 + 1) / \beta_0 \\
s_1 &= (\tau_2 - \alpha_2 + \alpha_1) / \beta_0 \\
s_2 &= (\tau_3 + \alpha_2) / \beta_0
\end{aligned}
\qquad (17)
$$

The necessary control effort may be determined from equation (14).

5 Training the Network

Training the ANN is a process which requires careful considerations of the network architecture and nature of the data [21,22]. Data vectors of real past plant outputs *y(t-i)* and past plant outputs *u(t-i)* [Fig. 2] generated by exciting the plant with a pseudo-random-binary-sequence of length N = 43 were employed as the training data set. The training was initiated by randomizing the network weights. Generally convergence in training took at most 300 iterations with a sampling time of 30 seconds. An optimum number of nodes in the hidden layer were experimentally fixed at four [Fig. 3]. The training regime used had a learning rate of 0.8 [Fig. 4] and momentum term of 0.95 .

6 Results

Figures 5 - 6 show the closed-loop responses obtained with NNW-PID control of the hot-spot temperature in a fixed-bed catalytic reactor. The NNW-PID controller performance improves with detuning, i.e. as the value of the tailoring polynomial coefficient τ_1 approaches the unit circle at minus one. This means that as the value of τ_1 approaches unity, the solution of the characteristic equation (14) results in a less active, more stable and therefore a more damped response of the controlled variable. This system behavior is shown at the extreme values of τ_1; note the oscillations in the control signal at $\tau_1 = 0$ and the damping as τ_1 approaches minus unity .

7 Conclusions

In this work a dynamic, online ANN process identifier that utilizes the weights of the network to determine the control effort of an NNW-PID controller to a real-world problem is employed. The control of a hot-spot temperature in a fixed-bed catalytic reactor system has been achieved using this approach.

Index: artificial neural networks, self-tuning control, Hot-spot temperature

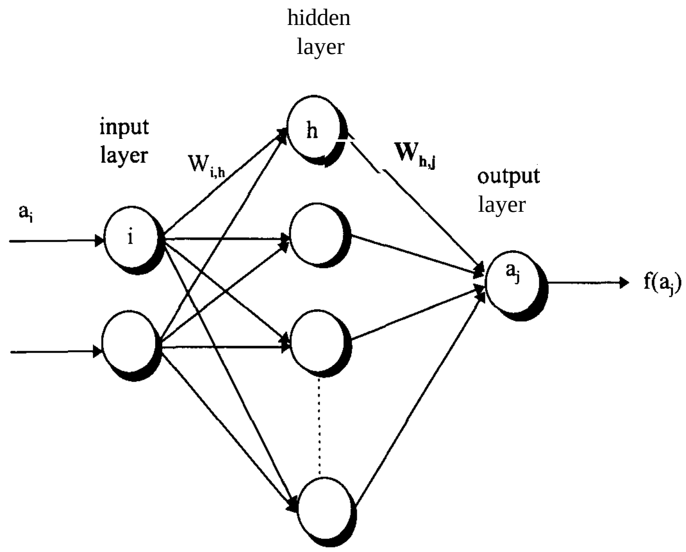

Fig. 1 General neural network topology

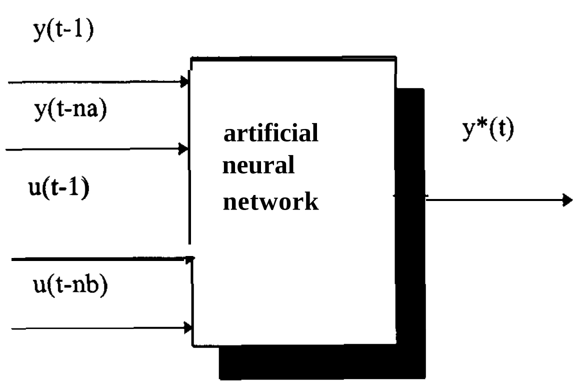

Fig 2. Input-output structure of the ANN

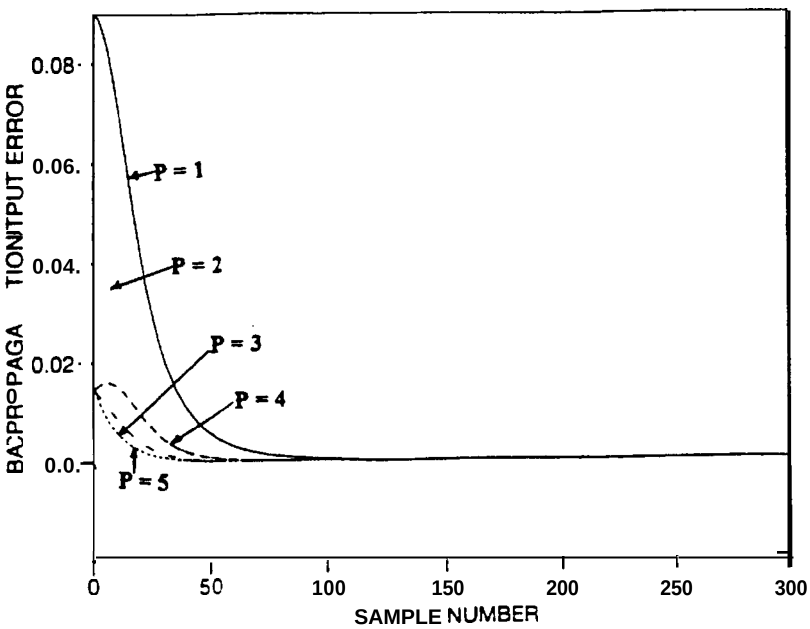

Fig 3. Backpropagation Learning
Varying no. of hidden nodes (P); Learning speed: g = 0.1

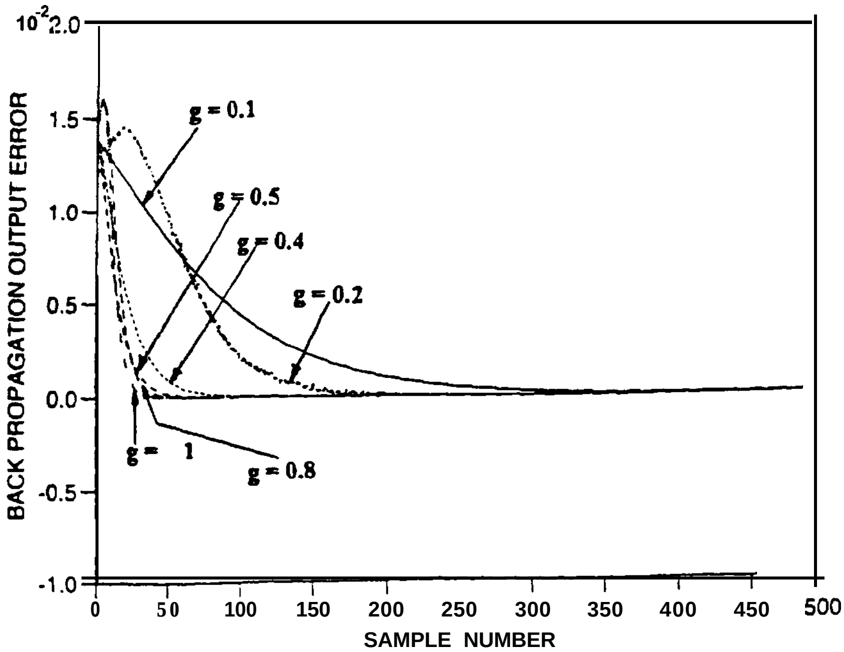

Fig 4. Backpropagation Learning
Varying learning rate (g); No. of hidden nodes P = 4

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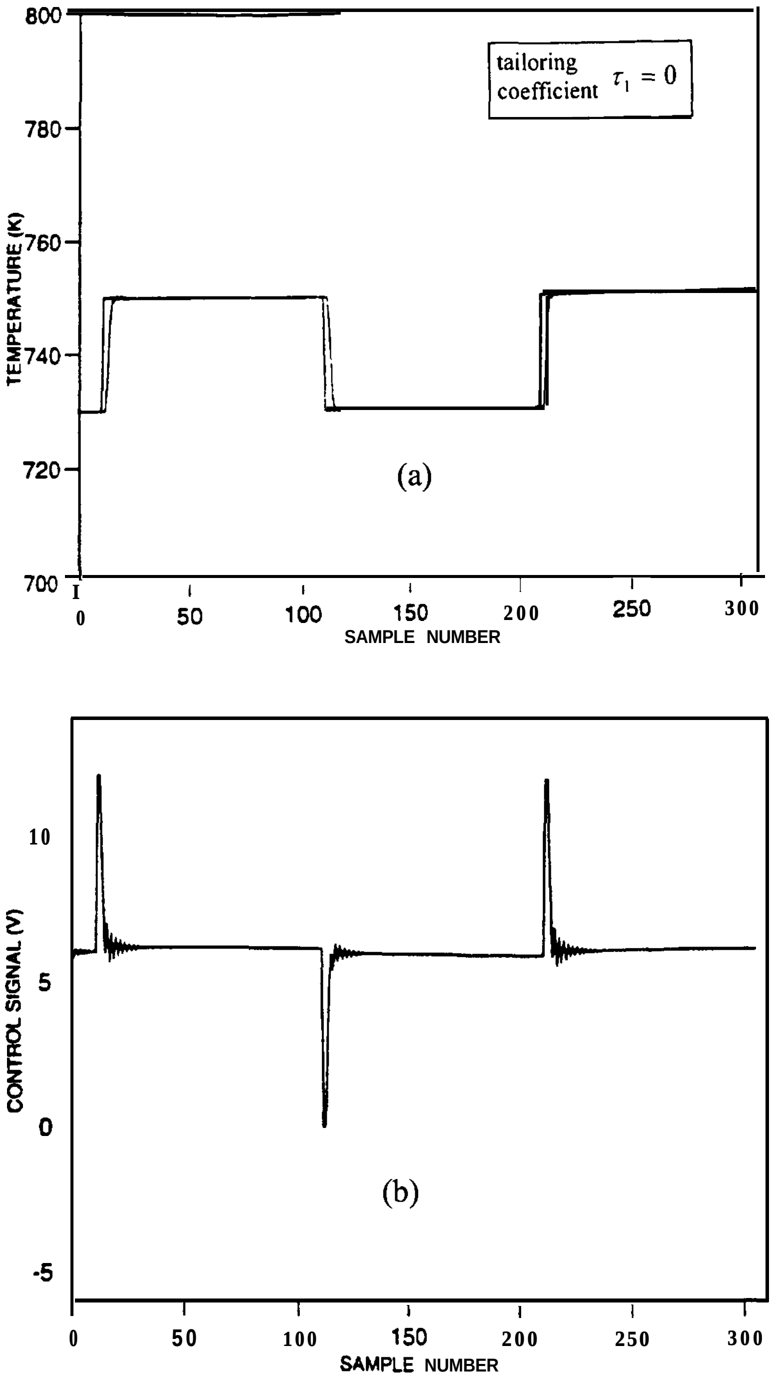

Fig 5 Neural Network STPID Control: τ , = 0
(a) Set point following case (b) Control signal

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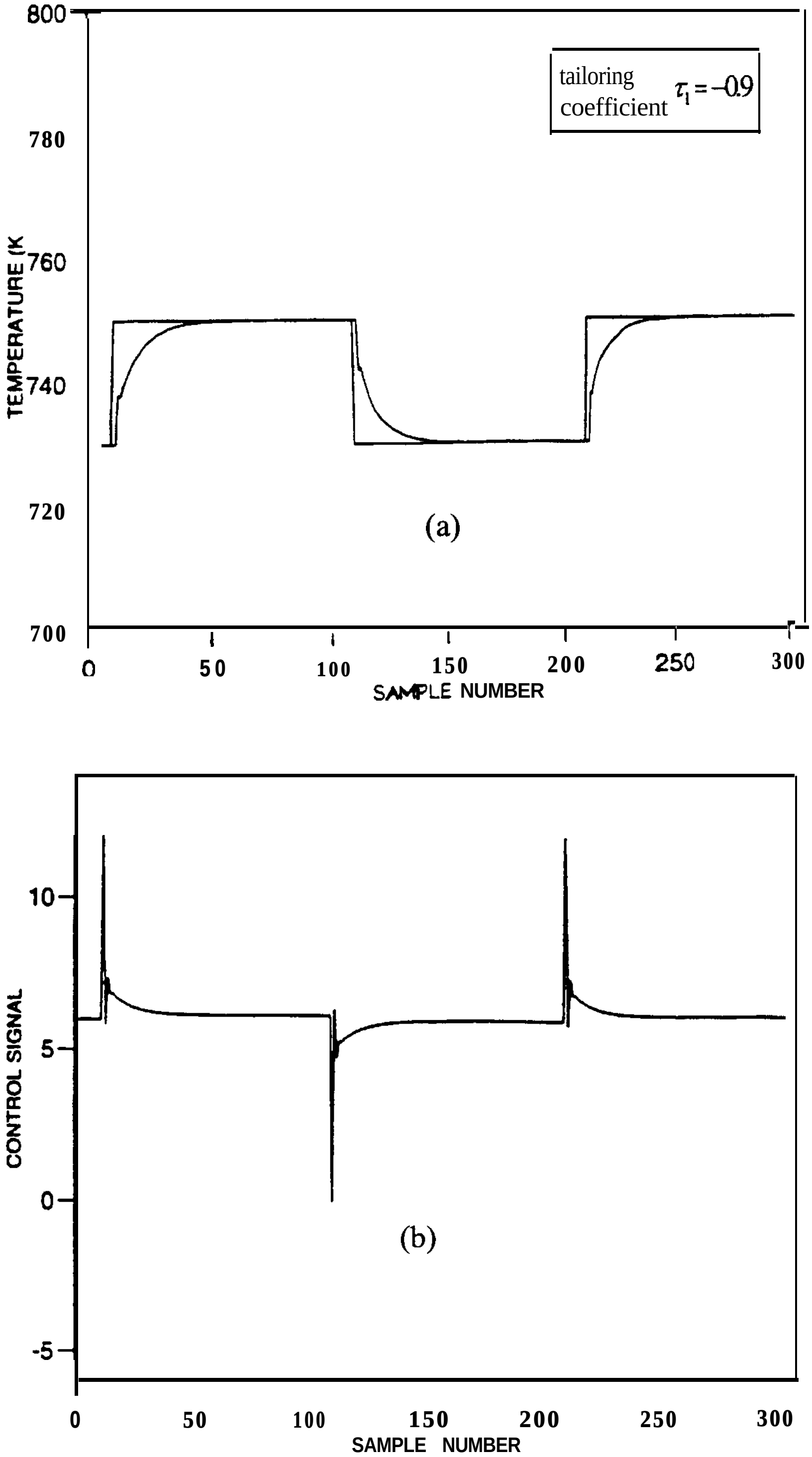

Fig 6 Neural Network STPID Control: $\tau_1 = -0.9$
(a) Set point following case (b) Control signal

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