Simulation Studies of Continuous Stirred Tank Reactor Using Artificial Neural Network Based Supervised Control Method

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Abstract

This paper focuses on the control of nonlinear chemical process plant common used devices in chemical industry, Continuous Stirred Tank Reactor (CSTR). The idea is to have a control system that will be able to achieve improvement in the level of conversion and to be able to track set point change and reject load disturbance. Two control schemes, PID control and ANN controller based supervised control are considered. The two schemes are studied for setup change, disturbance effect and model - plant mismatch. The comparison shows that artificial neural network (ANN) controller have a better perform than PID one, in the extreme range of non-linearity. The goal of this paper is to show that, provided with appropriate adaptation techniques and control structures, neural networks can be used to adaptively control a wide range of nonlinear processes at a useful level of performance. Simulation results are used for choosing of an optimal working point and an external linear model of this nonlinear plant.

Keywords: CSTR, PID; ANN; neural network; supervised control.

1. Introduction

Simulation is very important and popular tool nowadays, when computation speed of computers increases exponentially every day. Simulations on mathematical models has several advantages over the experiment on a real model or system. It is saving, cheaper and less time demanding [1]. Neural network technology has received much attention in the field of chemical process control, this is because of inherently non-linear nature of most of the processes and neural network have great capability for solving complex nonlinear mathematical problem. Neural networks have shown great progress in identification of nonlinear system. Due to above reasons the ANN technique is used in this paper to design an intelligent controller for chemical process [2].

2. Mathematical Model of Continuous Stirred Tank Reactor

Continuous Stirred Tank Reactors (CSTR) are common used because of their technological parameters. Reaction inside flows continuously and we can control this reaction by for example volumetric flow rate of the reactant. The first step is introducing of the mathematical model which describes relations between state variables in the mathematical way. This mathematical model comes from material or heat balances inside the reactor. In our case of isothermal reactor with complex reaction is mathematical model the set of ordinary differential equations (ODE). A continues stirred tank reactor (CSTR) is used to convert a reactant (A) to a product (B). The reaction is liquid phase, first order and exothermic. Perfect mixing is assumed. A cooling jacket surrounds the reactor to dissipate the heat of reaction. The model of the continuous stirred tank system and the operating point data (Refer Table 1) as specified in the Pottman and Seborg paper has been used in the simulation studies [3, 4].

Table 2.1: Steady state operating data

Process variable	Normal operating condition
Measured product concentration (C_A)	0.08235 mol/l
Reactor temperature (T)	441.81 K
Coolant flow rate (q_c)	100 l/min
Process flow rate (q)	100 l/min
Feed concentration ($C_{A\circ}$)	1 mol/l
Feed temperature ($T_\circ$)	350.0 K
Inlet coolant temp ($T_{C\circ}$)	350.0 K
CSTR volume (V)	100 l
Heat transfer term (hA)	7e+5 cal/(min.K)
Reaction rate constant ($k_\circ$)	7.2e+10 min^{-1}
Activation energy term (E/R)	9.98e+3 K
Heat of reaction (ΔH)	2e+5 cal/mol
Liquid density (ρ, ρ_c)	1e+3 g/l
Specific heats (C_p, C_{pc})	1 cal/(g.k)

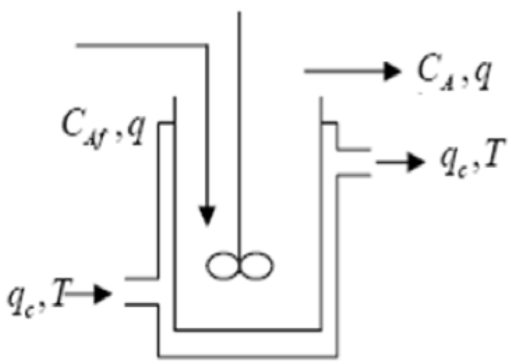


Figure 2.1: Continuous Stirred Tank Reactor

In the process considered for simulation study as shown in Figure 2.1, an irreversible, exothermic reaction $A \longrightarrow B$ occurs in constant volume reactor that is cooled by a single coolant stream.

The dynamic non-linear model is represented by two first-order non-linear differential equations. The first one simulates a material balance of the reactant A, the second equation describes a dynamic of enthalpy balance [3, 5]. The CSTR system has two state variables namely the temperature (T) and the concentration of the reactor (C_A). The process is modeled by the following equations:

$$\frac{dC_A(t)}{dt} = \frac{q(t)}{V}\left(C_{A\circ}(t) - C_A(t)\right) - k_\circ C_A(t)\, exp\left(-E/RT(t)\right) \tag{2.1}$$

$$\frac{dT(t)}{dt} = \frac{q(t)}{V}\left(T_\circ(t) - T(t)\right) - \frac{(-\Delta H)\, k_\circ C_A(t)}{\rho\, C_p}\, exp\left(-E/RT(t)\right) + \frac{\rho_c\, C_{pc}}{\rho\, C_p V} q_c(t)\left[1 - exp\left(\frac{-h\,A}{q_c(t)\rho C_p}\right)\right]\left(T_{c\circ}(t) - T(t)\right) \tag{2.2}$$

3. Simulation Results for Open Loop System

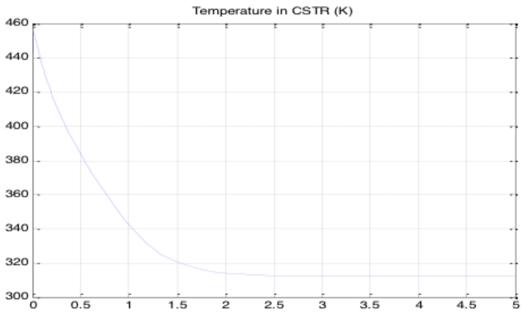
Figure 3.1a and 3.1b show the temperature and concentration response of the CSTR for the coolant flow rate as constant (q = 100 l/min), and the set point of control input is Temperature of cooling jacket (T_c = 290 K). Figure 3.2b and 3.2c show the temperature and concentration response of the CSTR for the coolant flow rate variation as shown in Figure 3.2a. From the open loop response of CSTR process it can be concluded that the dynamic behavior of the CSTR process is not the same at different operating points and the process is indeed non-linear. Form the simulation results the sharp peaks occur because the reaction is exothermic.

4. Control System Design

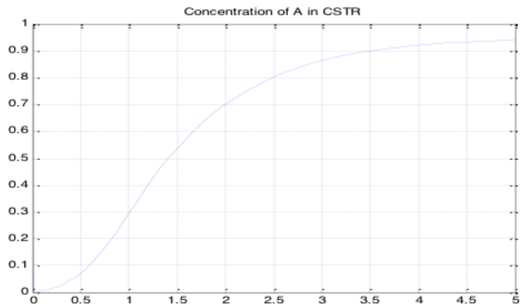
Processes with only one output being controlled by a single manipulated variable are classified as single-input single output (SISO) systems. It should be noted however, that most unit operations in chemical engineering have more than one control loop. In fact, each unit typically requires the control of at least two variables. e.g. product rate and product quality. There are therefore usually at least two control loops. Systems with more than one control loop take are known as multi-input multi-output (MIMO) or multivariable systems.

4.1. PID Controller

About 95% industrial control loops are still based on proportional K_P, integral K_I and derivative K_D (PID) controller; this is because of simplicity in its structure, robustness in its operation and ease of comprehension of its principle. However, most of



(a) Temperature response



(b) Concentration response

Figure 3.1: Open loop response of CSTR process

the industrial PID controllers deteriorate in performance when they are dealing with highly nonlinear process. PID controller gave optimal control for first order system without any delays. There are three classes of PID in this work; the class chosen has the generic form:

$$U(t) = K_P\, e(t) + K_I \int e(t)\, dt + K_D \frac{d}{dt} e(t) \quad (4.1)$$

The variable $e(t)$ represents the tracking error, the difference between the desired value $r(t)$ and the actual output $y(t)$. This error signal will be used by PID controller. PID will take appropriate action according to the law and pass the signal $U(t)$ to the plant to adjust the appropriate manipulated variable.

4.2. Design ANN Controller Based Supervised Control

It is possible to teach a neural network the correct actions by using an existing controller. This type of control is called supervised learning. But why would we want to copy an existing controller that already dose the job? Most traditional controllers are based around an operating point. This means that the controller can operate correctly if the plant operates around a certain point. Theses controllers such as PID controller will fail if there is any sort of uncertainty or change in unknown plant. The advantages of neuro-control are if an uncertainty in the plant occurs the ANN will be able to adapt its parameters and maintain controlling the plant when other robust controllers would fail.

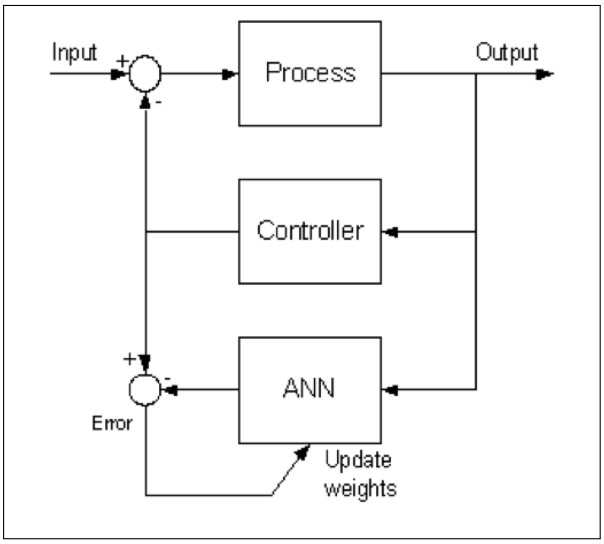
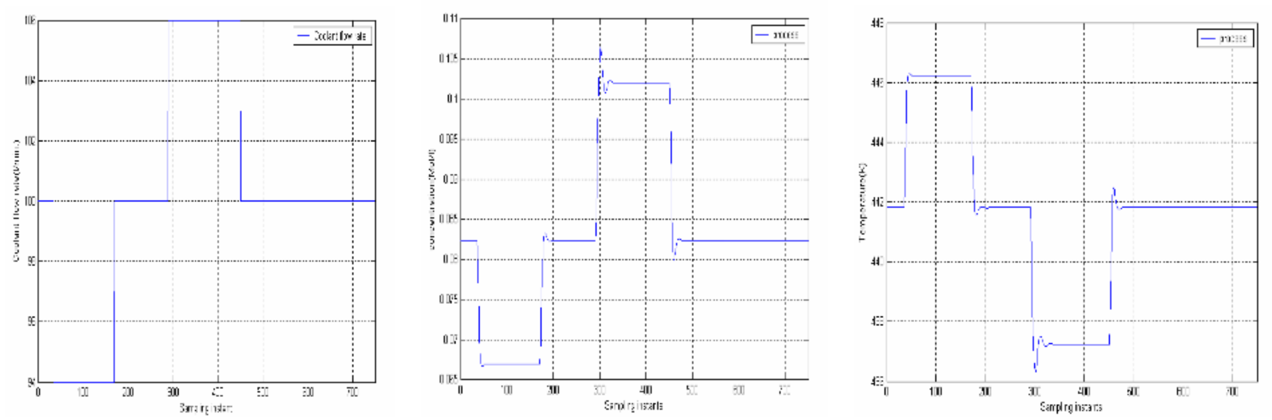


Figure 4.1: Supervised learning using an existing controller

In supervised control, a teacher provides the correct actions for the neural network to learn (Figure 4.1). In offline training the targets are provided by an existing controller, the neural network adjusts its weights until the output from the ANN is similar to the controller. When the neural network is trained, it is placed in the feedback loop. Because the ANN is trained using the existing controller targets, it should be able to control the process. At this stage, there is an ANN which controls the process similar to the existing controller. The real advantage of neuro-control is the ability to be adaptive online (Figure 4.2). An error signal (desired signal – real output signal) is calculated and used to adjust the weights online. If a large disturbance uncertainty occurs in the process - the large error signal is feedback into the ANN and this adjusts the weights so the system remains stable [10].



(a) Variation in control flow rate **(b)** Concentration response **(c)** Temperature response

Figure 3.2: Open loop response of CSTR process with variation in control flow rate

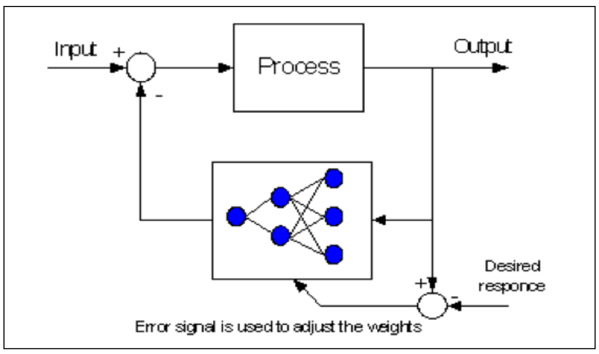


Figure 4.2: Adaptive neural control

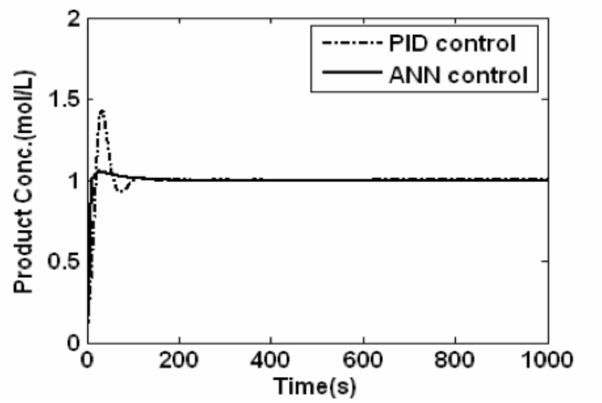


Figure 5.1: Closed loop response for the system under PID and ANN control

5. Simulation Results

Figure 5.1 shows response for both ANN and PID controller. For PID controller, the controller setting that gave the best performance was found to be $K_c = 5.5$, $K_i = 0.7$ and $K_d = 10$. The response is not without of overshooting, which is very high. For the case of ANN the overshoot is very small. The next performance test involved a set point tracking problem the set point was allowed to change in random fashion. Figure 5.1 show the result obtained using the ANN based supervised control strategy. The system behavior shows perfect tracking with no overshoot although the system is somehow sluggish which may be accommodated for the system under consideration.

The dotted line in Figure 5.2 shows the performance of a PID controller. Overshoot is observed and settling time for the first set point is quite long. But for the subsequent set points PID response looks similar to ANN with small over shoot. The plots also show an unsymmetrical response of PID control for different set points, implying that the system behave nonlinearly for PID control.

We now examine the system response in the presence of external disturbance. The system was disturbed by introducing 10% change in reference signal. The response obtained for this disturbance is shown in Figure 5.3, ANN controller was fast to arrest the disturbance but there is occurrence of overshoot the ANN was able to counteract faster the disturbance and return it to original condition. This is not without overshoot. The PID control gives serious oscillation and it did not settle throughout the simulation period.

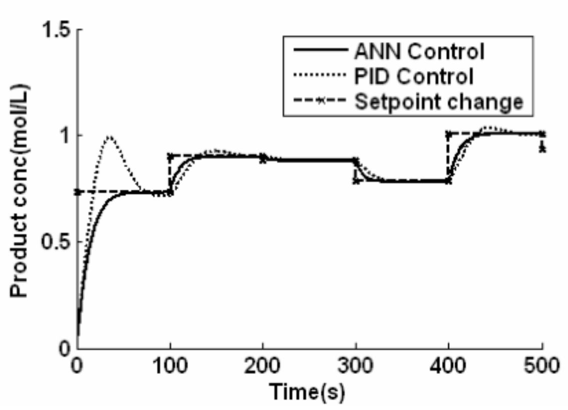


Figure 5.2: Closed loop responses for set point tracking for the system

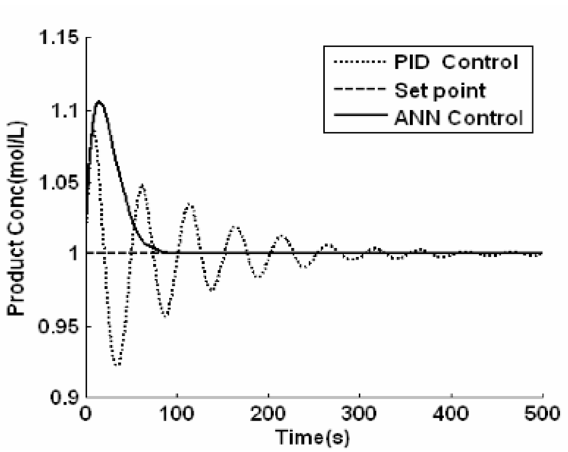


Figure 5.3: Closed loop responses of the in the presence of disturbance

6. Conclusion

From the results obtained in our simulation we can see that the ANN controller using supervised control was able to track set point change and reject the external disturbances. The responses were somehow sluggish in the faces of external disturbances but give no oscillatory behaviors. For PID controller, the performance deteriorated for set point changes and under the influence of external disturbances. This reason for poor performance can be adduced because of high nonlinearity of the CSTR. ANN control approach using references model to tailor system output to a desired response was developed. The controller has been able to take care of nonlinearly aspect of the system. ANN control scheme has better trajectory tracking ability than PID since the former is based on nonlinearity of the model, while the latter based on particular operating conditions. The control was able to adapt to system changes and operating condition change.

The transient BFCM should be improved to include the effect of the gas and liquid flow rates, the backmixing in the gas phase, variable backmixing ratio in the liquid phase across the static mixer.

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