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Control of Continuous Stirred Tank Reactor using Neural Networks

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Abstract

Background/Objectives: This paper presents the design of neuro controller NARMA-L2 for composition control in an isothermal Continuous Stirred Tank Reactor (CSTR) by manipulating the input feed composition. **Methods/Statistical Analysis:** The NARMA-L2 controller design is implemented in two stages in which the first stage is system identification to model the process and the second stage is designing the process controller. For controlling the product composition in the CSTR, the neuro controller NARMA-L2 is implemented in MATLAB Simulink environment. **Findings:** The simulation results show the superiority of the NARMA-L2 in accurately tracking the composition set-point changes in the CSTR and control the system better as compared to that of the conventional PID. The neuro controller NARMA-L2 can handle non-linear aspects of the CSTR by transforming its non-linear dynamic into an implicit algebraic model which can control the trajectory of the CSTR efficiently. **Application/Improvements:** The advantage of using the neuro controller NARMA-L2 is that it requires the minimal online computation compared to other neural network architecture for control such as model reference control and model predictive control.

Keywords: Continuous Stirred Tank Reactor (CSTR), Neuro Controller NARMA-L2, Neural Networks, PID, System Identification

1. Introduction

Continuous Stirred Tank Reactor (CSTR) is a common unit operation used in chemical plants and plays an important role in the field of chemical process industry technology. CSTR exhibits nonlinear behavior and usually has wide operating ranges. Nowadays, for the realization of flexible manufacturing capability and also increased competition, CSTR often operates to produce products that have different specifications[1]. However, CSTR often operates in a dynamic state, which makes it difficult to control. This condition occurs when the values of the variables in a process are constantly changing over time[2]. Therefore, a process control system should be built to ensure that CSTR operates at steady-state. Modeling is very helpful in control[3] and system optimization[4]. Accurate prediction of system behavior, either in dyamic or steady-state, is important in the design of a control system. Briefly, modeling is a mathematical technique that is applied to a process in order to build a good process control system[3] and it is useful for control and optimization of a chemical process[4]. Accurate prediction of the behavior of a chemical process, whether in a state of dynamic or steady state, is important in system design and process control[5].

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Nowadays, the conventional Proportional-Integral-Derivative (PID) control is often used in industries because the physical control parameter in PID controller is clear and easy to interpret. However, most of the chemical processes are designated as non-linear systems and generally; it is very difficult to find the optimal PID gain of the system that is not linear. Since the PID gain plays an important role in determining the nature of the control system, many tuning methods have been applied. However, most of these methods are for linear systems which are difficult to use in non-linear systems[4].

In recent years, computer intelligence has emerged as a very effective approach in solving problems faced in our lives. Among the many intelligent techniques designed and applied successfully are such as neural network, fuzzy logic and evolutionary programming. Neural network which is a model based on human brain information processing, has been widely considered in the chemical processing industry. Many controller design schemes have applied Artificial Neural Network (ANN) because it is effective for non-linear estimation and suitable for non-linear system[6]. Especially, in the chemical engineering systems, ANNs are widely used for modeling and process control. In this area, most of the techniques for control system known applied the black box modeling techniques which involve the use of non-linear model based on the input/output data. These techniques rely on the accuracy of the model and the availability of sufficient historical input/output data.

Neural networks are recorded to have been successfully used in identification and control of dynamic systems[7]. Universal approximation capabilities of the multi-layer perceptron model make it a popular option for modeling non-linear systems and to be implemented as non-linear controllers. From the chemical engineering literature, ANN has been applied for various engineering applications such as slippage detection, signal processing, modeling and process control[8]. There are several reasons for the wide application of ANN, firstly, the advancement in computer technology and parallel processing have made ANN to be used economically and feasible than before. Secondly, ANN consists of net basic functions which are non-linear, has the ability to develop a good process model of the data sample and requires little or no a priori knowledge of the duties to be performed. Thirdly, ANN has the potential to solve complex problems that cannot be solved by most conventional techniques[9].

Since conventional PID controller cannot be used effectively to control non-linear systems, an intelligent controller such as neuro controller NARMA-L2 is used in this research to control the product composition of CSTR. The proposed controller addresses to more general control problem which does not require mathematical model of the system under controlled and have the ability to approximate nonlinear system[10] which demonstrating the ability of handling non linearity. Among recent works carried out, neuro controller NARMA-L2 has been used to control diverse systems as bioreactor, coupled tank system, robot and power system[11–14]. In this work, process control of the CSTR using neuro controller NARMA-L2 will be studied, and compared with the conventional PID control. Process data pairs of input and output composition, generated from the CSTR model built based on the first principles model, are used to train the proposed ANN model.

2. Process Description

Consider a jacketed CSTR with two feed streams, components A and B that react isothermally to yield product C, as shown in Figure 1. Irreversible reaction with the following chemical reaction occurs:

$$A + B \rightarrow C$$

Table 1 refers to the process variables used in the CSTR and the process operating conditions are listed in Table 2.

The control objective of the CSTR is to regulate the product composition C by manipulating the feed composition of component A at constant temperature and volume. The principle of conservation of mass is used to develop the mathematical model for the CSTR. The model equations for the process are given as follows:

$$\frac{dh}{dt} = F_{in,1} + F_{in,2} - 0.2\sqrt{h} \tag{1}$$

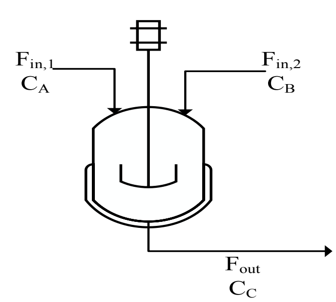

Figure 1. Diagram of CSTR process.

Table 1. Lists of variables

Variables	Comments
$F_{in,1}$	Feed flow rate of component A
$F_{in,2}$	Feed flow rate of component B
F_{out}	Output flow rate of product C
C_A	Feed composition of component A
C_B	Feed composition of component B
C_C	Output product composition of component C
h	Liquid level
k_1	Forward rate constant
k_2	Reverse rate constant

Table 2. CSTR Operating conditions

Variables and Parameter	Value
C_A	24.9 mol/l
C_B	0.1 mol/l
k_1	1 l/min
k_2	1 l/min

$$\frac{dC_c}{dt} = (C_A - C_c)\frac{F_{in,1}}{h} + (C_B - C_c)\frac{F_{in,2}}{h} - \frac{K_1 C_c}{(1+k_2 C_c)^2} \quad (2)$$

Non-linear mathematical model of the CSTR is converted into the MATLAB Simulink model as shown in Figure 2. This model is taken as the process plant system, and the data generated from this model is used for training the neural network. The model is a sub-system for process control CSTR.

3. Narma-L2 Control Design

Nonlinear Auto Regression Moving Average (NARMA-L2) model is a standard model representing a general discrete time non-linear systems. It is considered as the neural network architecture for control which is implemented in MATLAB Simulink. The main idea of this type of neuro controller is to change non-linear system dynamics into linear dynamics by canceling the nonlinearity. NARMA-L2 controller design is performed in two stages: first stage is system identification to model the process and second stage is designing the process controller. The system to be controlled is identified by using the NARMA-L2 model which is in the following form[15]:

$$\begin{aligned} y(k+d) &= f\left[y(k), y(k-1), \ldots, y(k-n+1), u(k-1), \ldots, u(k-n+1)\right] \\ &+ g\left[y(k), y(k-1), \ldots, y(k-n+1), u(k-1), \ldots, u(k-n+1)\right].u(k) \end{aligned} \quad (3)$$

where $u(k)$ and $y(k)$ are the system input and output, respectively. The non-linear functions $f(\ )$ and $g(\ )$ are approximated using neural networks by using a set of input-output data pairs and trained offline in batch.

This model is in companion form, where the next controller input, $u(k)$ is not contained inside the non-linearity and hence it can solve for the control input that causes the system output to follow the set-point. The block diagram of the identification of NARMA-L2 model is shown in Figure 3.

In the design of the neuro controller NARMA-L2, plant identification should be carried out before the controller training is executed. Figure 4 is the plant identification window to train the NARMA-L2 model in the MATLAB Simulink.

Neuro controller NARMA-L2 is trained using 2000 data pairs generated from the simulations of the CSTR Simulink model (Figure 2) which is implemented as a subsystem (plant) in the neuro controller NARMA-L2 as shown in Figure 5. The training epoch is set to 200. In this study, the Levenberg-Marquardt (LM) back propagation algorithm is used in the training of neural network. The control equation for the system is given by:

$$u(k+1) = \frac{y_r(k+d) - f\left[y(k), \ldots, y(k-n+1), u(k), \ldots, u(k-n+1)\right]}{g\left[y(k), .., y(k-n+1), u(k), \ldots, u(k-n+1)\right]} \quad (4)$$

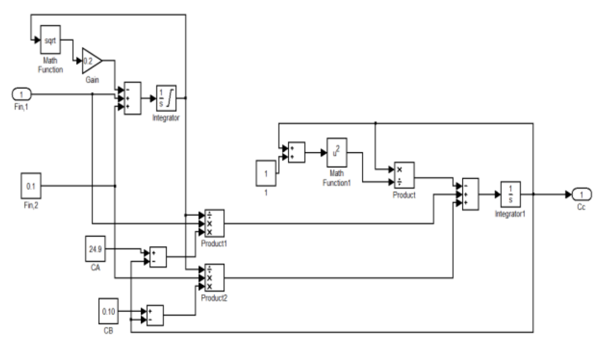

Figure 2. CSTR Simulink model.

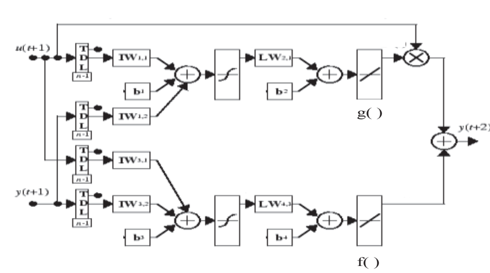

Figure 3. Identification of NARMA–L2.

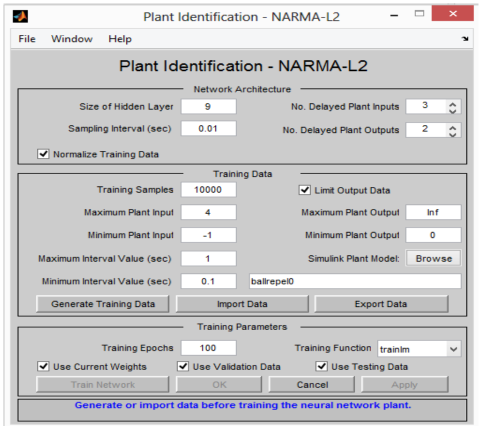

Figure 4. Identification of NARMA-L2 plant model.

where, $y_r(k + d)$ is the reference signal to be tracked. The controller is implemented with the previously identified NARMA-L2 process model, as shown in Figure 5.

4. PID Feedback Control Design

PID feedback control is used to control the concentration of the CSTR using the following control equation[16]:

$$m(t)=\bar{m}+\frac{k_c}{\tau_I}\int e(t)dt+k_c\tau_D\frac{de(t)}{dt}+k_c \quad (5)$$

where,

m(t): output control variable
$\bar{m}$: bias
K_c : controller gain
τ_I : integral time
τ_D : derivative time

These three parameters, K_c, τ_I and τ_D must be tuned to get satisfactory control. Figure 6 shows a block diagram of the control system using feedback controller. The above three parameters are tuned automatically using the PID Simulink blocks which are built in the MATLAB.

5. Results and Discussion

In this study, the mathematical model of the CSTR process is built using first principles modeling. This model is used for generating pairs of input and output data which is then used in process identification for training the NARMA-L2 model. Feedback controller and neuro controller NARMA-L2 are used to control the product composition C_C of the CSTR. Tests have been carried out to determine the ability of the controllers to track changes related to the set-point.

5.1 Process Identification of CSTR

The study on the different identification structures using 2000 input and output data (Figure 7) was carried out in order to find the optimal structure. The results obtained are tabulated in Table 3.

Comparison of the results obtained from process identification for the different ANN structures are tabulated in Table 4.

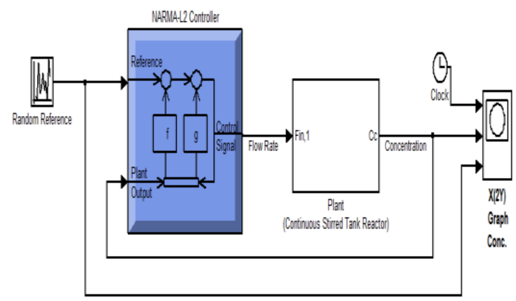

Figure 5. The block diagram for the NARMA-L2 controller.

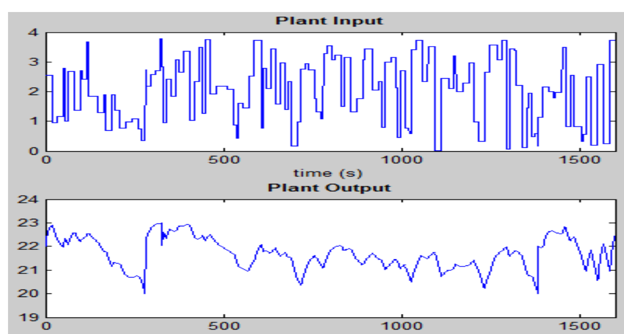

Figure 6. Block Diagram for the feedback controller.

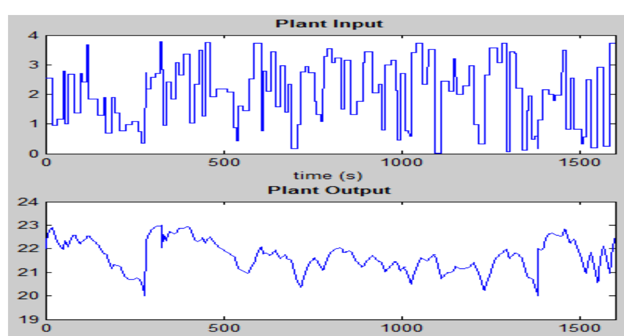

Figure 7. Neural network training data.

Table 3. Process identification structure for CSTR

Parameter	Structure			
	I	II	III	IV
Number of neurons in the hidden layer	7	5	7	7
Training function	LM	LM	LM	LM
Number of delayed plant inputs	2	2	3	2
Number of delayed plant outputs	2	2	3	2

Table 4. Comparison of identification structures trained with LM function

Parameter	Structure			
	I	II	III	IV
Validation performance	1.928×10^{-6}	0.3037	0.0617	7.94×10^{-6}
Epoch	200	9	125	68
Gradient	0.0011	0.0014	0.5081	0.0254
Mean squared error (MSE)	10^{-7}	0.01	0.01	10^{-5}
Regression (Training)	1	0.1310	0.9614	0.9999
Regression (Validation)	1	0.2632	0.9540	0.9999
Regression (Overall)	1	0.0887	0.9586	0.9999

Comparing the results of the four ANN structures, structure I is found to give the best structure with the least Mean Squared Error (MSE) of 1.0×10^{-7}. In addition, the neural network regression for the structure I is 1, indicating the goodness of fit of the model data. Thus, the structure identification process I is applied in the simulation to control the CSTR using the neuro controller NARMA-L2. The structure I consists of one hidden layer with 7 neurons and one output layer. The neural network trained using the parameter values obtained in structure I is as shown in Figure 8.

Figures 9 and 10 show the performance of the PID controller and the proposed neuro controller NARMA-L2, respectively, with respect to 1% step change in the concentration of component C. As shown in Figure 9, the PID controller cannot reach the new set point value, whilst Figure 10 shows the neuro controller NARMA-L2 responses with overshoots at first and then in a short time reaches the new set point value.

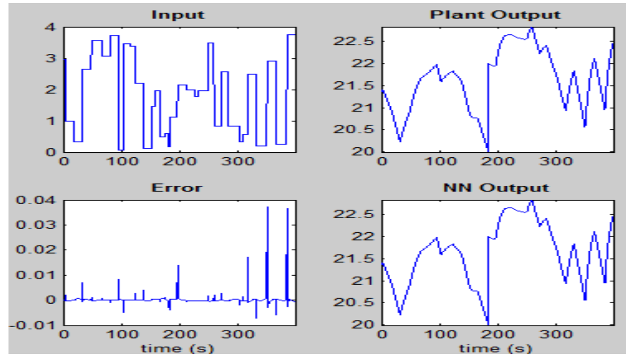

Figure 8. Neural network training results for CSTR process.

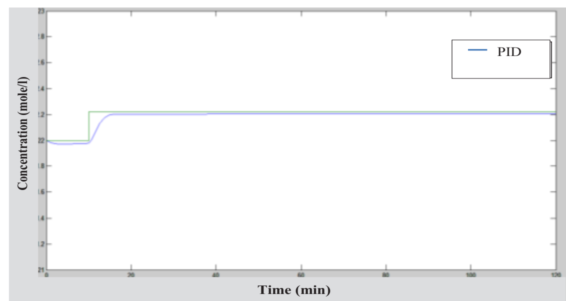

Figure 9. Concentration C_C response to 1% set point step change in the composition C_C using feedback PID controller.

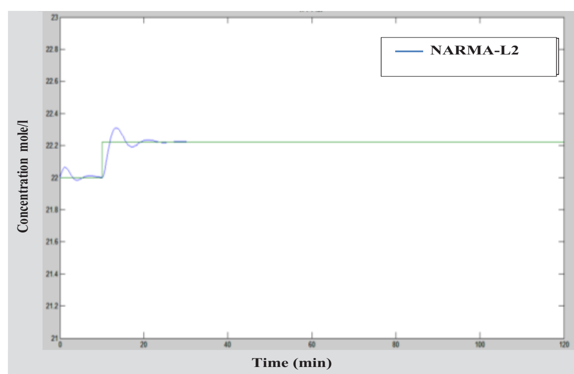

Figure 10. Concentration C_C response to 1% set point step change in the composition C_C using the neuro controller NARMA-L2.

Tests were also carried out to assess the ability to track changes in the controller set point where the set point is changed to the difference values. Figures 11 and 12 show the response in tracking the product concentration set point change in composition C_C with PID feedback controller and NARMA-L2 neuro controller, respectively.

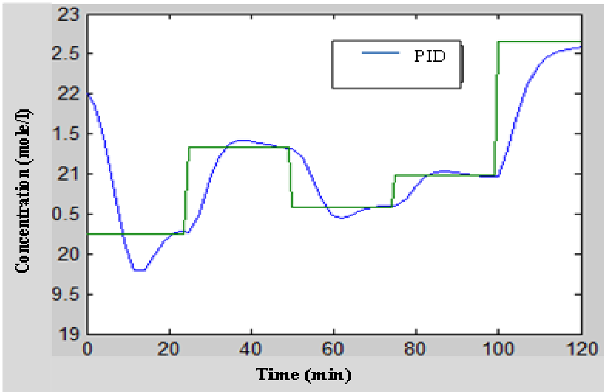

Figure 11. Product composition C_C set point tracking with PID feedback controller.

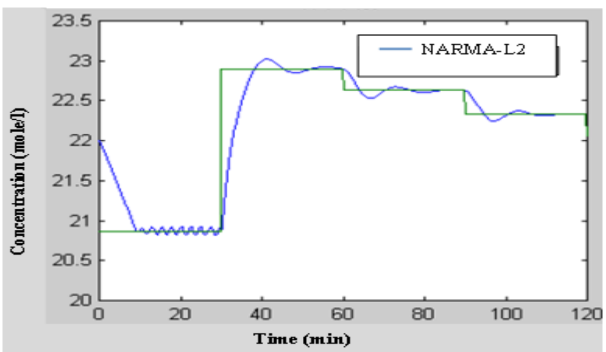

Figure 12. Product composition C_C set point tracking with Neuro Controller NARMA-L2.

The PID controller response indicates an overshoot at the first set point, response is slow with oscillation especially at the first, second, and fifth set points, and do not achieve stability in the simulation for the given time as shown in Figure 11. While the response of neuro controller NARMA-L2 in Figure 12 shows an overshoot at the first set point change only and subsequently shows a perfect set-point tracking. The neuro controller NARMA-L2 is superior compared to the PID controller in tracking the product composition C_C set-point changes in the CSTR. Therefore, the neuro controller NARMA-L2 has the ability to control the product composition C_C of CSTR better than the conventional PID controller.

6. Conclusion

The neuro controller NARMA-L2 is found to be more precise and give better response compared with the conventional PID feedback controller in controlling the product composition of the CSTR. The results demonstrate the superior ability of the neuro controller NARMA-L2 in tracking the changes in the product composition set point in a short period compared with the PID controller. This is due to the fact that the neuro controller NARMA-L2 can handle non-linear aspects of the CSTR by transforming its non-linear dynamic into an implicit algebraic model which can control the trajectory of the CSTR easily and efficiently.

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