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NEURAL NETWORK BASED PREDICTIVE, NARMA-L2 AND NEURO-FUZZY CONTROL FOR A CSTR PROCESS

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Abstract:

In recent years, there has been an expansive growth in the study and implementation of neural networks over a spectrum of research domains. Neural network based Predictive control is recognized as an efficient methodology to address difficult control problems. The NARMA model is an exact representation of the input-output behaviour of finite dimensional non-linear discrete time dynamical systems in the neighbourhood of the equilibrium state. There has been a significant increase in the number of control system techniques that are based on nonlinear concepts. With the increasing research activities in the field of structural control, many control methods have been proposed and implemented. These methods are fuzzy control, optimal control, pole placement, sliding mode control, etc. Designing an effective criterion and learning algorithm for find the best structure is a major problem in the control design process. The fusion of ideas from fuzzy control and neural networks had acknowledged a significant role in improving controller performances. Fuzzy logic has proven effective for complex, nonlinear and imprecisely defined systems. Neural network derives its computing power through it's massively distributed structure and its ability to learn and therefore generalize. The fuzzy logic and neural networks can be integrated to form a connectionist adaptive network based fuzzy logic controller. To implement Neural network based Predictive and NARMA-L2 control, first step is modeling of the process for system identification and the second step is the controller design. Neural network based Predictive controller, NARMA-L2, Neuro fuzzy logic controller are implemented for a CSTR process and their performance are compared.

Keywords: System identification, Predictive control, NARMA-L2 control, Neuro fuzzy, CSTR process.

1. INTRODUCTION

Proportional-Integral-Derivative (PID) controllers have been used extensively in process industries due to their simple structure for control of multivariable processes. The reason why PID controllers have gained such popularity is that the controller can be tuned by means of simple rules of thumb, and detailed knowledge about the system is not necessary. PID controllers have been usedextensively in the chemical industries since they are simple, are often effective and represent the basic building blocks available in many process control systems. The basic PID controllers have difficulty in controlling processes with complex nonlinearity. To date, many sophisticated algorithms have been used to help the PID controller work under such difficulties ([1], [2]). One method is to adjust the PID parameters by ANN ([3], [4]). In the paper [5], an adaptive neural network controller for the control ofnonlinear dynamical system is proposed. This approach is adaptive in structure, and unlike standard adaptive controllers, uses no explicit model of the process in the design. Traditional neural networks are not practical in adaptive environments because of the large number of weights normally associated with them. In this structure, the controller network has very few connection weights and hence is well suited for real-time implementation.

Recent research indicates that more emphasis has been placed on the combined usage of fuzzy systems and other technologies such as neural networks to add adaptability to the design of control systems. Currently, most of the nonlinear control based methods use simplified models to decrease complexity of the algorithms. Considering the complexity of practical CSTR process, more realistic model with lesscomputation time is required for effective robust control over a wide range of operating conditions. Totake advantage of the representational capacity of Fuzzy Logic to incorporate experts' knowledge and the ability of Artificial Neural Network to fine tune this information by applying appropriate learning techniques, these two paradigms are combined and used to design an adaptive neurofuzzy logic controller (NFLC) based on online trained neural networks. Both these techniques, i.e., ANN and fuzzy logic, havetheir unique advantages and disadvantages. The integration of these two approaches can give improved results. The objective of design process is to find optimal structure/gains of the Robust and OptimalNeuro- Fuzzy Controller (NFLC). The control signal thus obtained will minimize a performance index, which is a function of the tracking/regulating errors, the quantity of the energy of the control signal applied to the system, and the number of fuzzy rules.

Model Predictive Control has been popular in industry because of the following advantages; it uses a model to evaluate how control strategies will affect the future behavior of the plant, its ability to hold process interactions and unusual dynamic response, it does not require rigorous models [6].To implementNARMA-L2 control, first step is modelling of the process for system identification. Here the controller is the rearrangement of the plant model and is represented in the companion form. Approximate methods are used for realizing the neural controllers to overcome computational complexity. Training algorithm used is backpropagation with early stopping technique.The objectives of the present work are to control a CSTR process using NN based Predictive control, NARMA-L2 control and Neuro fuzzy control and compare their performance. Modeling of the process is carried out using Levenberg-Marquardt algorithm, which is a modification of standard backpropagation algorithm.

II. Problem Description

Chemical processes are nonlinear and have been controlled using linear models. However, controllers based on linear models do not perform well for highly nonlinear situations [7]. Several methods have been proposed to deal with the nonlinearity. Most of these methods are based on fundamental models, in the form of differential equations. The nonlinearities of practical processes are usually very complex. It is quite difficult to derive complete knowledge of such nonlinearities [8]. Neuro Network based controllers has been applied for identification and control of such nonlinear processes. Consider a first order exothermic Continuous Stirred Tank Reactor (CSTR) having the controlled variable as concentration ofoutlet product while the manipulated variable as the coolant flow rate to the cooling jacket.

The mass and energy balance equations for the exothermal process are described by the following differential equations.

$$\dot{x}_1 = -x_1 + D_a(1-x_1)e^{[x_2/(1+x_2/\gamma)]} - d_2 \qquad \ldots\ldots(1)$$

$$\dot{x}_2 = -x_2 + \mu D_a(1-x_1)e^{[x_2/(1+x_2/\gamma)]} + \beta(u - x_2) + d_1 \qquad \ldots\ldots(2)$$

$$y = x_1 \qquad \ldots\ldots(3)$$

where x_1 and x_2 are the extent of reaction and the dimensionless temperature of the reactor contents respectively. u is the input which is the dimensionless flow rate of the heat transfer fluid through the cooling jacket. D_a is the Damkohler number, d_1 and d_2 are the dimensionless disturbance variables in feed temperature and feed concentration [5]. The parameters used for simulation studies are $D_a = 0.072$, $\mu = 8.0$, $\beta = 0.3$ and $\gamma = 20.0$. The amplitude of the input signal is bounded between - 0.65 and 0.65 $(0.65 < u < 0.65)$ and the output of the system is between 0 and 1. The sampling time used is one dimensionless time unit.

III. PREDICTIVE CONTROL

The two steps involved when using neural networks for control system are System identification and Control design. In the system identification stage, the neural network model of the plant to be controlled is developed. In the control design stage, the neural network plant model is used to design the controller. The advantage of using Artificial Neural Networks to simulate the process is that after they are trained, they represent a quick and reliable way of predicting their performance. They can also be continuously updated.

The neural network plant model of a non-linear plant is used to predict future plant performance. The controller then calculates the control input that will optimize plant performance over a specified future time horizon. The first step in model predictive control is to determine the neural network plant model (system identification). Next, the plant model is used by the controller to predict future plant performance.

The model predictive control method is based on the receding horizon techniques. The neural network model predicts the plant response over a specified time horizon. The predictions are used by a numerical optimization program to determine the control signal that minimizes the following performance criteria over the specified horizon.

$$J = \sum_{j=N_1}^{N_2} (y_r(t+j) - y_m(t+j))^2 +$$

$$\rho \sum_{j=1}^{N_u} (u'(t+j-1) - u'(t+j-2))^2 \ldots\ldots(4)$$

Where N_1, N_2 and N_u define the horizons over which the tracking error and the control increments are evaluated. The u variable is the tentative control signal, Y_r is the desired response and Y_m is the network model response. The ρ value determines the contribution that the sum of the squares of the control increments has on the performance index.

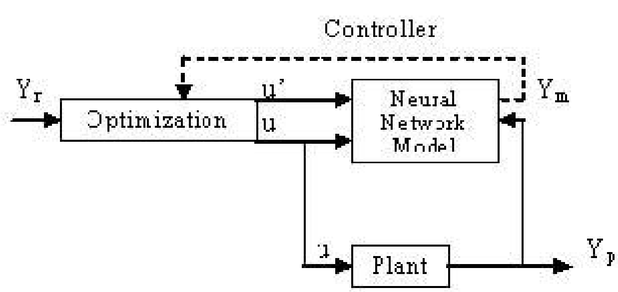

Fig.1 Block Diagram of NPC

The architecture of the Neural Network used for identification is 5-9-1. The whole training procedure uses 10,000 iterations. The corresponding model validation and testing data are shown in Fig. 2 and Fig. 3.

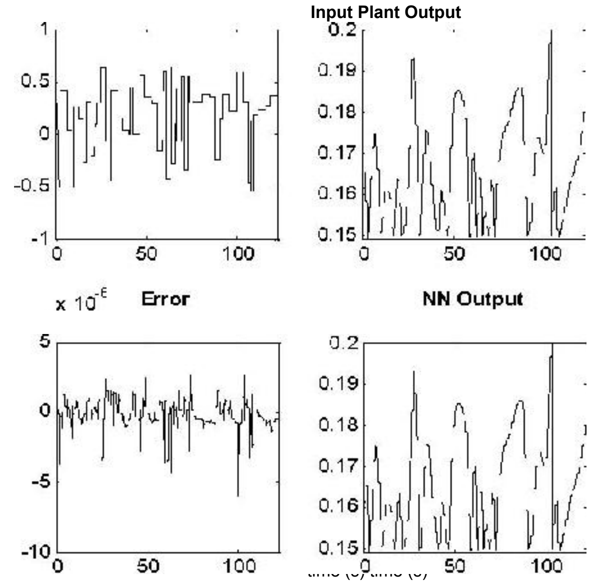

Fig. 2 Validation of the identified Neural model

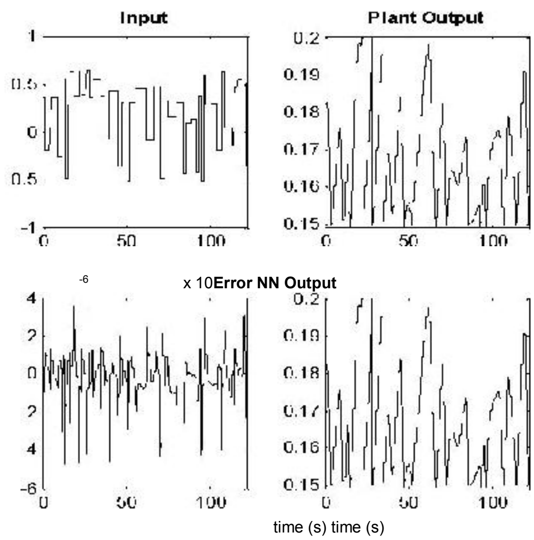

Fig. 3 Testing of the identified Neural model

IV.NARMA-L2 CONTROL

NARMA-L2 is one of the neural network architecture that has been implemented in the MATLAB for prediction and control. NARMA-L2 controller design is performed by two stages. 1. System identification and 2. Control design. In the system identification stage, the neural network model of the plant which is to be controlled is designed. For controller design, the plant model which is identified is used. The neurocontroller designed is referred by two different names. (i) NARMA-L2 control and (ii) Feedback Linearization control. When the plant model is in companion form, then it is said to be NARMA-L2 control and when the plant model can be approximated by companion form is feedback linearization control. In NARMA-L2 control, the controller design is simply the rearrangement of plant model, which is trained offline, in batch form. It requires the least computation than model predictive and model reference controllers. If neural network is used as a controller, the parameters of NARMA-L2 have to be adjusted to achieve on line control. Only approximated methods are used in practice for controlling a plant represented by a NARMA-L2 control which reduces computational complexity. The desired input can be computed algebraically from the identification model and hence a separate controller neural network is not needed in NARMA-L2 controller. The model outputs are very close to the actual plant output in NARMA-L2 which implies that the identification error is marginally less. In adaptive control problems where the plant parameters are assumed to be unknown, NARMA-L2 makes the estimation procedure straight forward. [9]

a. SYSTEM IDENTIFICATION

In system identification, modelling of the plant is the initial stage. Nonlinear Auto Regressive Moving Average (NARMA) model is the standard model that has been used to represent general discrete time nonlinear systems. NARMA model is represented by $y(k+d) = Ny(k), y(k-1),....$

$...., y(k-n+1), u(k), u(k-1),... ..., u(k-n+1)$ ……(5) Where u(k), and y(k) are the system input and output respectively and N is the nonlinear function. The Neural network plant model uses previous inputs and previous outputs to predict future value of the plant model. Since the process is slow, approximated NARMA-L2 model is used.

$\hat{y}(k+d) = f[y(k), y(k-1),... ...y(k-n+1), u(k-1),.... ..u(k-m+1)] + g[y(k), y(k-1),.. ...y(k-n+1), u(k-1),.. ..., u(k-m+1)].u(k)$…(6)

This model is in companion form, where the next controller input u(k) is not contained inside the nonlinearity. Advantage of this form is that the control input can be solved that causes the system output to follow the reference $y(k+d) = y_r(k+d)$.

b. CONTROLLER DESIGN

In NARMA-L2 controller, design is simply the rearrangement of plant model. Approximated NARMA-L2 model is

$\hat{y}(k+d) = \hat{f}[y(\kappa),.....y(\kappa-n+1), u(\kappa-1),.. .u(\kappa-m+1)] + g[y(k), y(k-1),.... ..y(k-n+1), u(k-1),....u(\kappa-m+1)]u(\kappa)$ …….(7)

When $\hat{y}(k+d) = y_r(k+d)$, then the next control input

$$u(k) = \frac{y_r(k+d) - f[y(k), y(k-1), \ldots .., y(k-n+1), u(k-1), \ldots u(k-n+1)]}{g[y(k), y(k-1), \ldots, y(k-n+1), u(k-1), \ldots.., u(k-n+1)]} \quad \ldots.(8)$$

Direct use of this equation can cause realization problems, because of control input u(k) determination is based on the output at the same time y(k), where d>2. The block diagram of NARMA – L2 controller is shown in Fig.4.The output error is used to adjust the neural network through a dynamic procedure. This approach combines the advantages of adaptive control and neural networks and is considered as a basic form to design a neurocontroller.

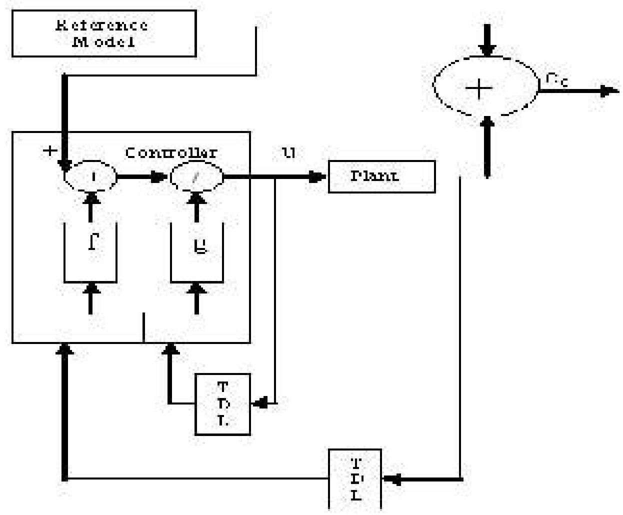

Fig.4 Block diagram of NARMA-L2 control

A three layer feedforward network is used to represent the forward dynamics of the system. Here the model, predicting the actual state is used. The Architecture of the neural network model used for identification is 5-20-1, where two of the input nodes are used for shifted feedback signals from the output of the network. One node can be used as bias and remaining nodes for shifted input signal. The training function used for the neural network is trainlm [10]. The neural network plant model uses previous inputs and previous plant outputs to predict future values of plant output. The whole training procedure uses 10,000 iterations. The resulting responses of model validation and test are shown in Fig.5. and Fig.6. The Mean-Square Error of the training is shown in Fig.7.

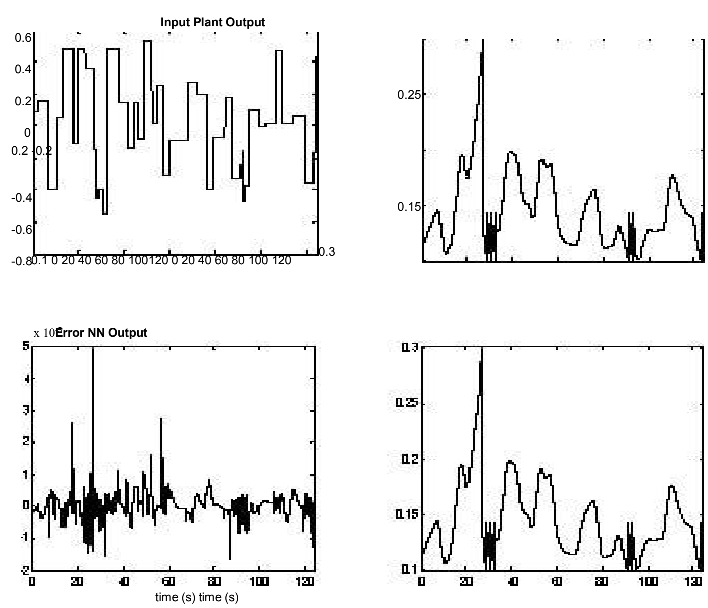

Fig. 5 Validation of the identified neural model

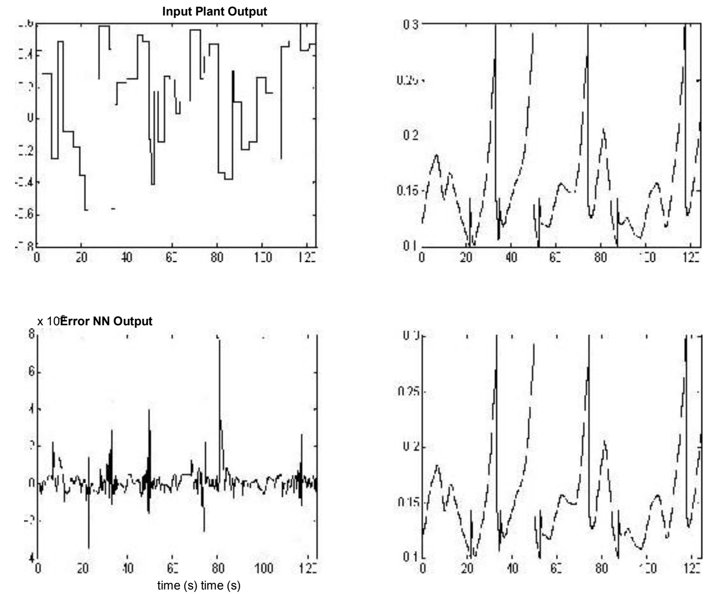

Fig. 6 Testing of the identified neural model

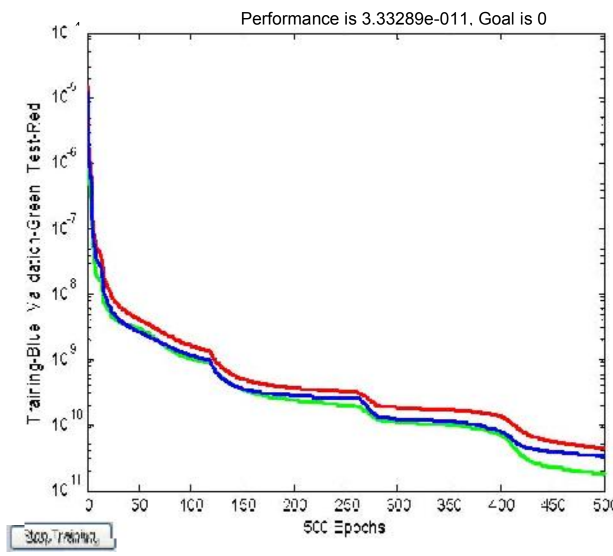

Fig. 7 Mean square error of the training

V. NEURO FUZZY LOGIC CONTROL

The Adaptive PI based Neuro-Fuzzy based controller is designed with two inputs, the error signal e and its integral quantity, and one control output (u). The training data is viewed to be very complex hence seven linguistic variables for each input variable were used to get the desired performance. The linguistic variables are specified by Gaussian membership functions and as a result 49 rules are devised. The rule-base contains the fuzzy IF-THEN rules of sugeno's first order type proposed by C.T. Lin and C.S.G.Lee(1991) in which the output of each rule is a linear combination of input variables plus a constant term. Thefinal output is the weighted average of each rule's output.

NFLC Architecture

The architecture of the NFLC sensing the input signals error and its integral error and its controller structure is shown in Fig. 8. where node functions in each layer are as described below.

Layer 1:Each node in this layer is an adaptive node performing Gaussian membership function.

$$o_{1,i} = \mu_{A_i}(x_i) = \exp\left[-\left(\frac{(x_i - c_{ij})}{\sigma_j}\right)^2\right]$$

where i=1, 2…7, j=1, 2...7 ----(9)

x_i, is the input to this layer and , is c_{ij} the center of the membership function.

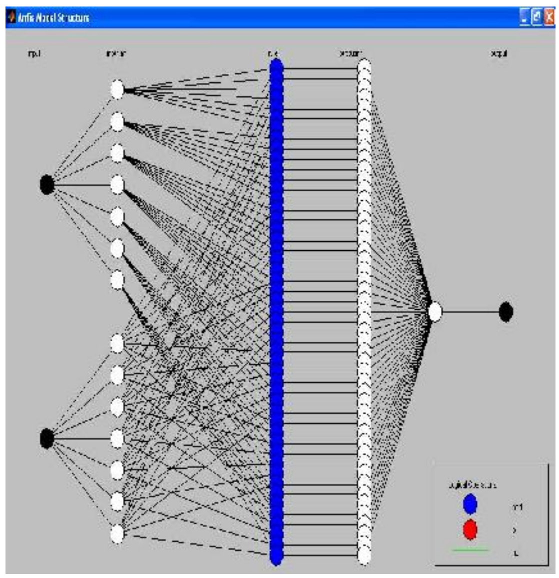

Fig. 8. Architecture of NFLC Layer 2:

Every node in this layer represents the firing strength of the rule.

$$o_{2,i} = w_i = \mu_{A,i}(x_i) \wedge \mu_{B,i}(y_i)$$

i=1…7. Eventually the nodes of this layer perform fuzzy AND operation. Layer 3: The nodes of this layer calculate the normalized firing strength of each rule.

$$o_{3,i} = \bar{w}_i = \frac{w_i}{\Sigma w_i}$$

i=1…49. w_i –firing strength of a rule. Layer 4: The nodes in this layer output the weighted consequent part of the rule table.

$$o_{4,i} = w_i f_i = w_i (p_i x_1 + q_i x_2 + r_i)$$

i=1,…49 where $\{p_i, q_i, r_i\}$ is the parameter set of this node.

Layer 5:

The single node in this layer computes the overall output as the summation of all the incoming signals.

$$O_{5,i} = \sum_i w_i f_i \Big/ \sum_i w_i \qquad i=1\ldots49.$$

where $O_{5,i}$ denote the output of the i^{th} node in layer 5.

VI. Simulation Study of CSTR Process

To determine the mathematical model of the process, process reaction curve method is used. The transfer function is obtained as

$$Gp(s) = \frac{0.667\ e^{-0.79}}{2.7497\ S + 1}$$

PI controller is designed using Cohen-coon method. The tuning parameters of PI controller are given in Table 1. Table 1. Tuning parameters of PI controller

Kc	4.8212
Ti(sec)	1.6534

For computer simulation, the CSTR nonlinear model is implemented using s-function and SIMULINK facilities in MATLAB. The basic time unit is seconds (sec) and continuous sampling was done.

Case i

The CSTR process set point concentration is changed from 0.15 mol/l to 0.19 mol/l. The resultsare shown in Fig.9 and the proposed NARMA-L2 controller settles quickly compared to predictive, neuro-fuzzy and PI controller. Also the overshoot is less for the proposed controller.

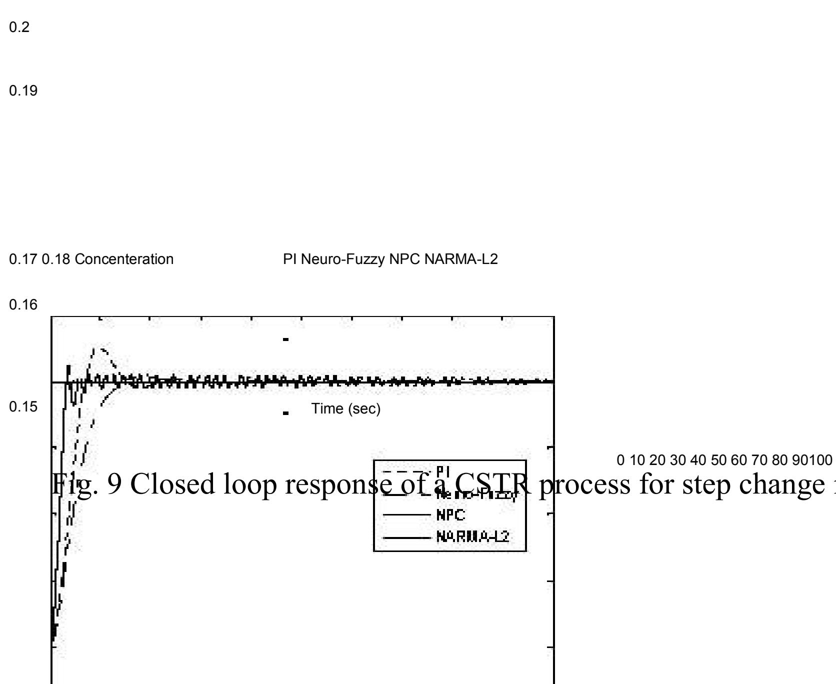

Fig. 9 Closed loop response of a CSTR process for step change in concentration from 0.15 to 0.19

Case ii

A step change of concentration is made from 0.15 mol/l to 0.20 mol/l for the CSTR process set point. The results are shown in Fig.10 and the proposed NARMA-L2 controller settles quickly compared to neural network based predictive, neuro-fuzzy and PI controller. Also the overshoot is less for the proposed controller.

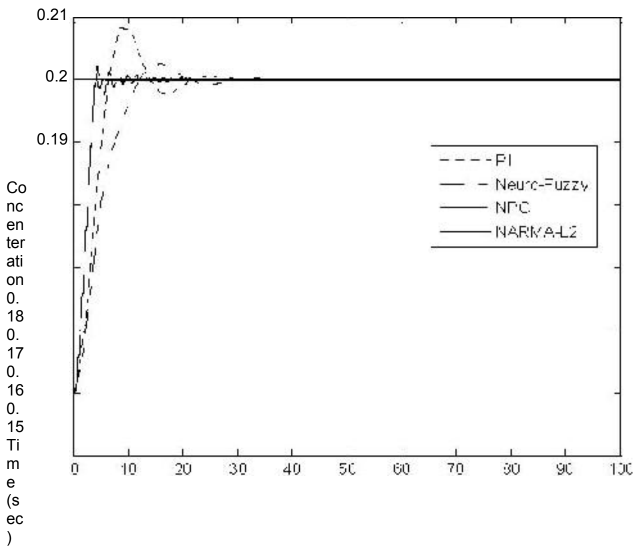

Fig.10. Closed loop response of a CSTR process for step change in concentration from 0.15 to 0.20

Case iii

A variation of concentration is made decrease from 0.15 mol/l to 0.21 mol/l for the CSTR process set point. The results are shown in Fig.11 and the proposed NARMA-L2 controller settles quicklycompared to neural network based predictive, neuro-fuzzy and PI controller.

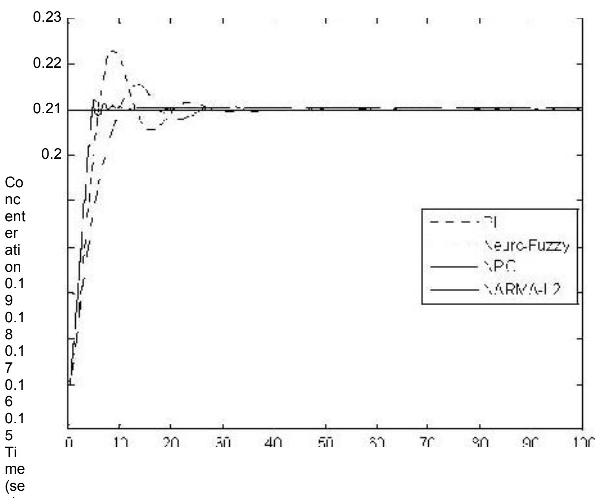

Fig.11. Closed loop response of a CSTR process for step change in concentration from 0.15 to 0.21

Case iv

The servo response in Fig.12 changes from from 0.15 mol/l up to 0.22 mol/l concentration of the CSTR process. It should be noted that the set-point C(t)=0.22 is very close to the instable region of CSTRprocess, in which there is only small overshoot. It validates the proposed controller developed based on NARMA-L2.

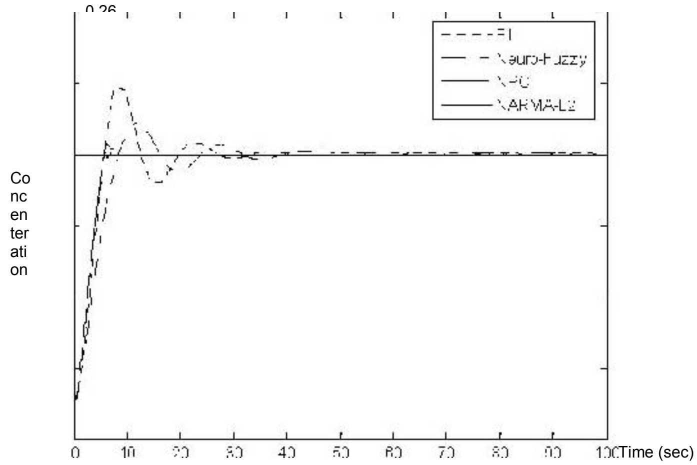

Fig.12. Closed loop response of a CSTR process for step change in concentration from 0.15 to 0.22

The behaviour of the NPC, NARMA-L2, NFLC and PI controller is shown in Fig.9-12, for various case studies and from which we can see the smooth transient response for NFLC compared to PI controller when the set-point C(t) changes. The comparative results are tabulated in Table.2 and are proved that the proposed NARMA-L2 controller is superior to NPC, NFLC and PI controller for the CSTR process under study.

Table .2 Comparative Performance Analysis

Set Point	Settling Time				Overshoot			
	PI	NPC	NARMAL2	NFLC	PI	NPC	NARMAL2	NFLC
0.15 to 0.19	27.00	25.2	4.6	24.5	0.1945	0.192	0.19096	0.191
0.15 to 0	39.50	32.15	5.1	30.00	0.209	0.2045	0.20009	0.203

The Table 3.shows the error performance analysis Integral Square Error (ISE), Integral Absolute Error(IAE), Integral Time Absolute Error (ITAE), of NARMA-L2, Neuro-Fuzzy and PI controller. The analysis shows that the proposed NARMA-L2 controller gives better performance compared to other controlling techniques under study.

Set Point		0.15 to 0.19	0.15 to 0.20	0.15 to 0.21	0.15 to 0.22
ISE	PI	0.00446	0.006791	0.00840	0.01359
	NPC	0.00341	0.00534	0.00684	0.00914
	NARMA L2	0.002292	0.004154	0.00721	7.2
	NFLC	0.00546	0.007864	0.00912	0.01441
IAE	PI	0.008995	0.01157	0.01431	0.01892
	NPC	0.00715	0.01062	0.01179	0.01462
	NARMA L2	0.003982	0.005801	0.00841	0.01106
	NFLC	0.0082	0.01295	0.01523	0.01925
	PI	0.1799	0.2314	0.2934	0.3785
	NPC	0.09851	0.1478	0.2017	0.2619

VII. CONCLUSION

A neural network based predictive control, NARMA L2 control, PI Control and Neuro fuzzy logic control are designed and implemented for the CSTR process and their performances are analyzed. Neural Network model has captured the input-output relationship throughout the entire operating range of the process. On comparing the performance, it is observed that NARMA-L2 controller is faster and has good set point tracking capability. Unlike other kinds of neural control schemes, which usually need more than one neural network for modeling and control, the NARMA-L2 control strategy uses just one for both modeling and control.

NOMENCLATURE

D_a - Damkohler number e - Difference between the input and target n - Net input to each node N_2 - Cost horizon N_u - Controller horizon p - Inputs on nodes t - Target vector u - Manipulated variable v - Performance index for the network W - Weight Matrix y_m - Neural model output y_p - Process output y_r - Reference model output α - Search parameter β - Dimensionless heat transfer coefficient γ - Dimensionless activation energy ρ - Controller weighting factor μ - Dimensionless adiabatic temperature rise.

ABBREVIATIONS

ANN - Artificial Neural Network CSTR - Continuous Stirred Tank Reactor. NARMA - Nonlinear Auto Regressive Moving Average Model NPC - Neural Predictive Control NFLC - Neuro Fuzzy Logic Control PI - Proportional Integral

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