International Journal of Soft Computing and Engineering (IJSCE)
ISSN: 2231-2307, Volume-3 Issue-5, November 2013

Comparative Performance Analysis of PID Based NARMA-L2 and ANFIS Control for Continuous Stirred Tank Reactor

Bharti Panjwani, Vijay Mohan

Abstract— This paper deals with two intelligent control schemes based on artificial neural network for temperature control in a jacketed Continuous Stirred Tank Reactor. Objective is to regulate the reactor temperature for an exothermic reaction taking place in the CSTR by manipulating the thermal condition of jacket. PID based NARMA-L2 and PID based ANFIS controller are designed and their performances are analyzed and compared. The simulation results show the priority of ANFIS control over NARMA-L2 control to achieve better response.

Keywords— Continuous Stirred Tank Reactor (CSTR); Nonlinear Auto Regressive Moving Average (NARMA); Adaptive-Network-Based Fuzzy Inference System (ANFIS); PID.

I. INTRODUCTION

Continuous stirred tank reactor (CSTR) exhibits quite non-linear dynamic behaviour offering a diverse range of researches in this field. The nonlinearities can be complex and the performance of conventional control techniques under such condition suffers. It is generally difficult to obtain an accurate model because of the inherent complexity of the chemical processes [1]. In recent years intelligent controls such as Fuzzy, Neural Network and Neuro Fuzzy have been of very interest for identification and control of such systems.

Neural Networks possesses approximation and generalization capability which makes it ideal for control of chemical processes. It is due to generalization that neural network based controller is able to respond satisfactorily to the data it is not trained with [2]. Furthermore neural networks have potential to map input- output dynamics of the system if adequately trained thus providing it capability to approximate functions, which is exploited for system identification.

Neural Network based NARMA-L2 controller is implemented by using two training methods namely, Levenberg-Marquardt algorithm and Scaled Conjugate Gradient algorithm for set point tracking in a CSTR. The results show Scaled Conjugate Gradient algorithm outperforms Levenberg-Marquardt algorithm [3]. A comparative study of U Model based NAIMC and a NARMA-L2 controller is presented in [4] and its advantages over a parallel scheme for adaptive control that uses one neural network is shown. Results also show that NARMA performs better than U Model based NAIMC.

Manuscript Received November, 2013.

Bharti Panjwani, Department of Instrumentation & Control Engineering, National Institute of Technology, Jalandhar, India.

Vijay Mohan, Department of Instrumentation & Control Engineering, National Institute of Technology, Jalandhar, India.

Fuzzy control is based on adept knowledge of the process rather than model based, but it has several drawbacks which led to development of adaptive fuzzy control techniques for non linear processes [5][6].

The control design by the combination of the neural predictive and the neuro fuzzy controller to control CSTR is implemented. The neuro fuzzy and the neural predictive controller work in parallel, where the neuro fuzzy adapts the output of the predictive controller, in order to enhance augured inputs [7]. The controller is implemented based on a Mamdani and Sugeno type fuzzy system. The ANFIS, which is a fuzzy inference system, is designed in the framework of adaptive networks. Simulation results show ANFIS outperforms other controls [8].

In this paper we introduce PID based, NARMA-L2 and ANFIS control schemes for the regulation of reactor temperature in a jacketed CSTR. The simulation results show that ANFIS control is better as compared to NARMA-L2 control.

II. MATHEMATICAL MODEL OF CSTR SYSTEM

We consider a first order exothermic reaction to take place in the jacketed Continuous Stirred Tank Reactor where a reactant A is converted to product B as shown in Fig. 1. In a jacketed CSTR the heat is added or removed because of temperature difference between jacket fluid and the reactor fluid [9], so taking the controlled variable as reactor temperature while the only manipulated variable being the jacket temperature. The jacket is assumed to be perfectly mixed and at lower temperature than the reactor thus removing the heat generated during the exothermic reaction.

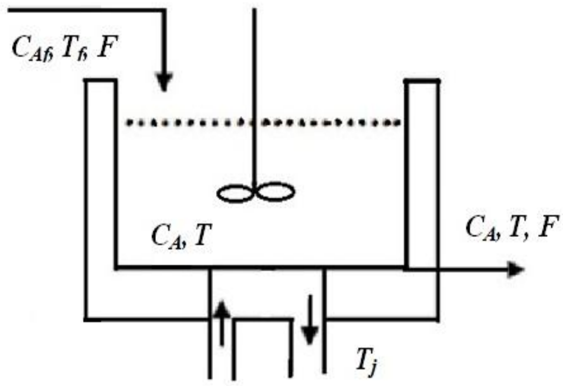

Fig. 1: Jacketed Continuous Stirred tank Reactor Model

For deriving system dynamics the mass and energy balance over the jacket and the reactor vessel is utilized and is described by the following set of differential equations.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

$$V\frac{dC_A}{dt} = FC_{Af} - FC_A - Vr_A \quad (1)$$

Where V is the constant liquid reactor volume, C_A is concentration of component A in the reactor, F is the flow rate and r_A is the rate of reaction per unit volume. Arrhenius expression for the first order reaction gives the rate of reaction as

$$r_A = k_0\left(-\frac{E_a}{RT}\right)C_A \quad (2)$$

Here k_0 is the frequency factor, E_a is the activation energy, R is the ideal gas constant and T is the reactor temperature. The reactor energy balance by assuming constant volume, constant heat capacity (c_p) and constant density (ρ) gives,

$$V\rho c_p\frac{dT}{dt} = F\rho c_p(T_f - T) + (-\Delta H)Vr_A - UA(T - T_J) \quad (3)$$

Where –ΔH is the heat of reaction, U is the heat transfer coefficient, A is the heat transfer area, T_f is the feed temperature and T_j is the jacket temperature. State Space Model obtained from (1), (2), (3) is

$$\frac{dC_A}{dt} = f_1(C_A, T) = \frac{F}{V}(C_{Af} - C_A) - k_0\left(-\frac{E_a}{RT}\right)C_A \quad (4)$$

$$\frac{dT}{dt} = f_2(C_A, T) = \frac{F}{V}(T_f - T) + \frac{(-\Delta H)}{\rho c_p}k_0\left(-\frac{E_a}{RT}\right)C_A - \frac{UA}{V\rho c_p}(T - T_J) \quad (5)$$

Steady state solution is found from (4), (5) by substituting the values of the parameters as specified in TABLE I, to obtain C_{As} and T_s.

TABLE I. REACTOR PARAMETERS VALUE

Parameter	Values	Unit
E_a	32.400	Btu/lbmol
k_0	$16.96*10^{12}$	hr^{-1}
U	75	Btu/hrft^2 °F
ρc_p	53.25	Btu/ft^3 °F
R	1.987	Btu/lbmol°F
F	340	Ft^3/hr
V	85	Ft^3
C_{Af}	0.132	lbmol/ft^3
T_f	60	°F
A	88	ft^2
–ΔH	39000	Btu/lbmol

III. CONTROLLER DESIGN

A. PID based NARMA-L2 control

Fixed Stabilizing control scheme [2] is utilized for implementing PID based Neural Network controller. In this paper a PID controller is used as the stabilizing feedback controller. From Fig. 2, it is seen that the total input to CSTR system is the sum of the feedback control signal and the feed forward control signal, which is calculated from NARMA-L2 neural network controller.

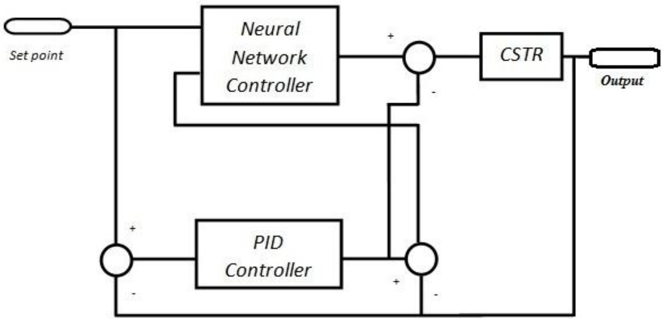

Fig. 2: PID based NARMA-L2 control structure

The NARMA-L2 controller uses the set point as input and feedback control signal as error signal to learn and adapt from it. As input advances NARMA-L2 takes over the control from PID controller. The advantage of such scheme is that Neural Network controller can start directly with stabilized system and so faster response can be obtained.

1. Design of PID

PID is a feedback type conventional controller which stands for Proportional-Integral-Derivative. The error (e) between set-point and the measured variable is used to generate proportional, integral and derivative action, whose weighted sum is then used as control variable (CV) for the CSTR. The weight of each action is decided according to the independent gain parameters P, I, D. The transfer function used for PID controller in this paper is [13]

$$G_1(s) = \left[P + I\left(\frac{1}{s}\right) + D\left(\frac{Ns}{s+N}\right)\right] \quad (6)$$

Where, the filter coefficient N sets the location of the pole in the derivative filter. PID controller is designed in MATLAB Simulink environment and gain parameters P, I and D, are found by Ziegler Nichols tuning method.

2. Design of NARMA-L2

NARMA-L2 is one of the Neural Network architecture for control, which is simply a rearrangement of the plant model. NARMA-L2 stands for Non Linear Auto Regressive Moving Average model and is referred when the plant model is approximated by companion form. If the plant model is in companion form it is known as feedback linearization technique. Designing of NARMA-L2 controller is done in two stages: System Identification, followed by Control Design.

System Identification means inferring a neural network model of the process to be controlled from a set of input-output data collected from the process, i.e. training a neural network to represent the forward dynamics of the system. A standard model structure used to represent general discrete time nonlinear systems is NARMA model [3][13].

$$y(k+d) = N\,[\,y(k), y(k-1), \ldots, y(k-n+1), u(k), u(k-1), \ldots, u(k-n+1)\,] \quad (7)$$

Where u (k) and y (k) are the system input and output respectively and N is the nonlinear function. During the identification, neural network is trained to approximate N and the neural network model created predicts the future plant outputs. Furthermore, the system output to follow the reference $(k+d) = y_r(k+d)$, controller is designed based upon NARMA-L2 approximate model and is shown in (8). The block diagram of NARMA-L2 controller is shown in Fig.3.

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

In the presented paper, NARMA-L2 controller is implemented in MATLAB Simulink. Five thousand data pairs of input and output temperature are generated from the CSTR model with sample time of 0.01sec for training neural network and are shown in Fig. 4.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

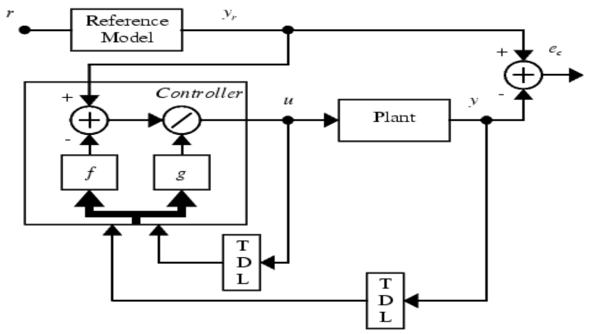

Fig.3: Block diagram of NARMA-L2 controller

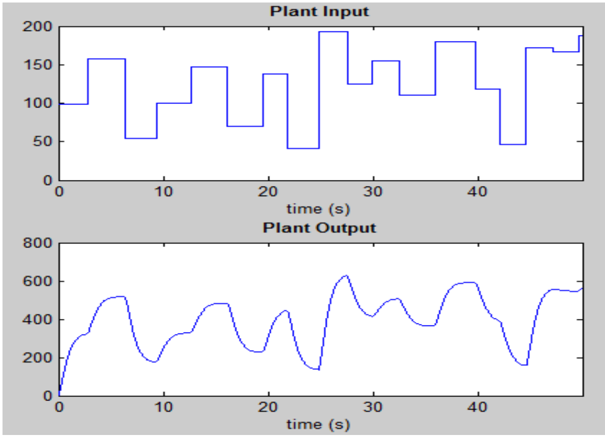

Fig. 4: Training data plot for NARMA-L2 controller

The neural network controller consisting of 3 hidden layers, 2 delayed input and 3 delayed outputs is trained offline in batch form with Levenberg-Marquardt algorithm using trainlm function [11]. Levenberg-Marquardt is approximation of Newton's method and is fastest back-propagation algorithm in MATLAB NN toolbox. Training process uses 100 iterations; and mean square error is used as performance which reduces as the training of the network advances and is shown in Fig. 5. Final control schematic of Neural Network controller is implemented based on fixed stabilization technique with structure as shown in Fig. 2.

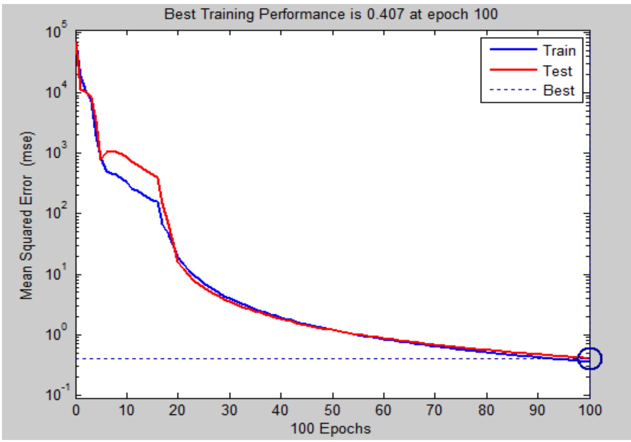

Fig. 5: Mean square error of the training

B. *PID based ANFIS control*

ANFIS, proposed by J.S.R. Jang [10][12], is a connectional simulation of the fuzzy system concept and T-S inference model. For this system we use two inputs and one output, first order T-S model to design the ANFIS control structure as shown in Fig. 6.

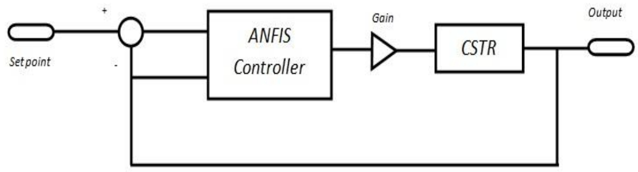

Fig. 6: ANFIS control structure

The two inputs to the ANFIS controller are: (1) PID controlled reactor temperature as error input, and (2) error to PID controller as rate of change of error. Firstly we need to acquire the training data from PID control structure shown in Fig. 7.

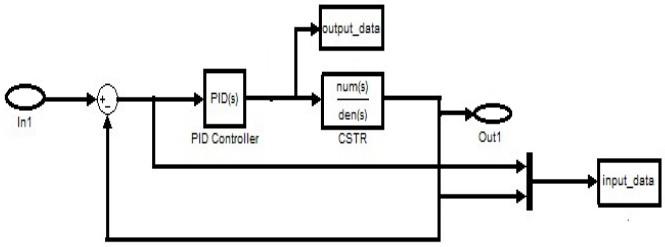

Fig. 7: PID control structure

To collect 1501 samples of inputs and output data pairs, use of ode3 solver is done with step size of 0.01sec and simulation time 15sec. Finally, the data is loaded into anfiseditor as shown in Fig. 8.

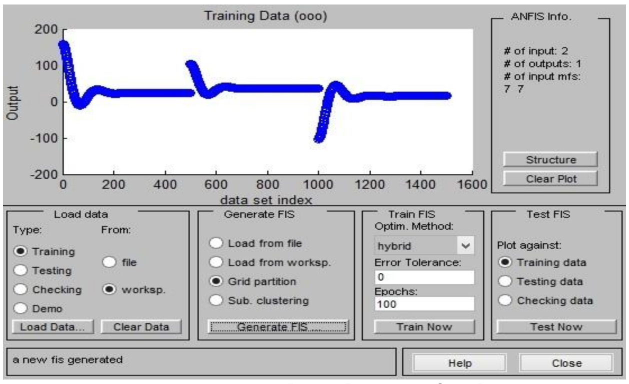

Fig. 8: Training data plot in anfiseditor

FIS file using grid partition with seven Gaussian membership functions for each input and linear output is generated. Finally, the FIS file is trained with hybrid optimization, taking error tolerance zero and performing hundred iterations. Training error comes out to be 5.5349 as shown in Fig.9. The control rule surface view of ANFIS controller is shown in Fig. 10.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

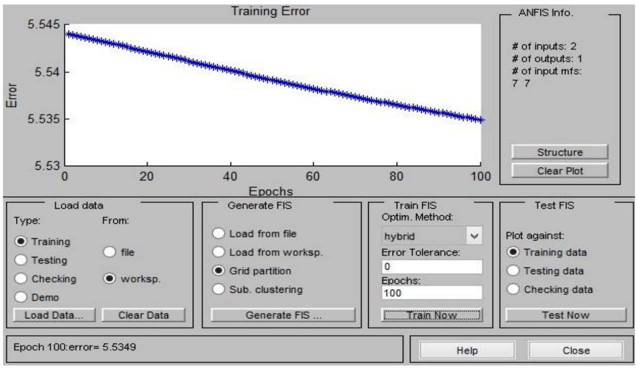

Fig. 9: Training error plot and training error

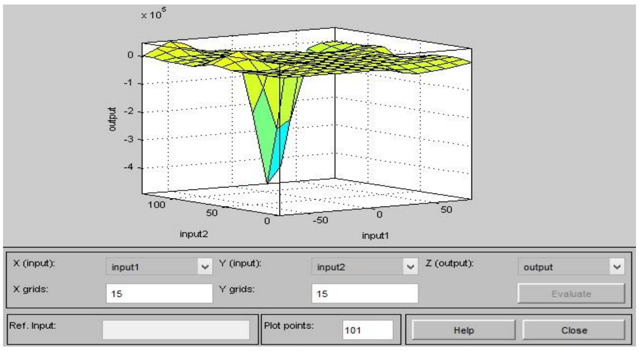

Fig. 10: Control surface rule view of ANFIS

IV. SIMULATION AND RESULTS

For controlling the reactor temperature in a jacketed CSTR, PID based NARMA-L2 and ANFIS controllers are successfully implemented in MATLAB Simulink environment. Simulation results for set point of 80^{o}F are shown in Fig. 11. The time domain specifications for temperature regulation in CSTR equipped with the proposed controllers are specified in TABLE II.

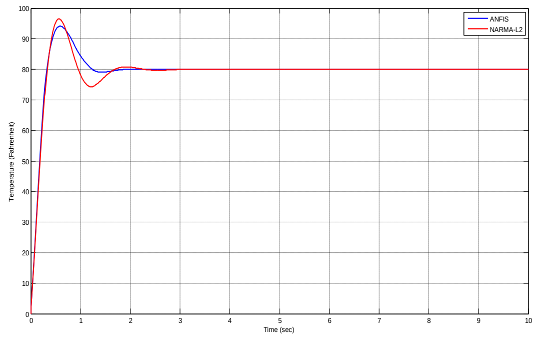

Fig. 11: Time response of NARMA-L2 and ANFIS control

TABLE II. SUMMARY OF THE PERFORMANCE CHARACTERISTICS

Time domain specification	ANFIS controller	NARMA-L2 controller
Settling time (sec)	1.9	2.2
Overshoot(%)	17.5%	19.6%
steady state error (e_{ss})	0	0

Furthermore the reference tracking capability of the proposed controllers for varying set point temperature in CSTR is shown in Fig.12.

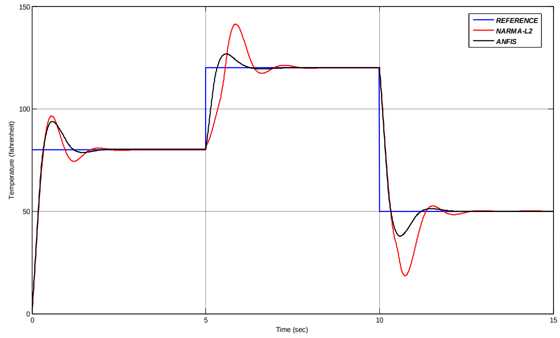

Fig. 12: Reference tracking performance of NARMA-L2 and ANFIS control

V. CONCLUSION

In this paper, NARMA-L2 and ANFIS controller are successfully implemented for control and regulation of temperature in a Continuous Stirred Tank Reactor. Simulation results show that ANFIS control has improved set point tracking capability as compared to the NARMA-L2 control.

ACKNOWLEDGMENT

We would like to express our gratitude towards our guide and mentor Mr. Narinder Singh for his valuable advice, positive criticism, and consistent encouragement. We would also like to thank our families for their blessings, moral and emotional support and valuable feedback, without which this work would not have been completed.

REFERENCES

1. T. Zhang and M. Guay, “Adaptive Nonlinear Control of Continuously Stirred Tank Reactor Systems”, Proceedings of the American Control Conference Arlington, VA June 25-27, 2001, pp.1274-1279.
2. Martin T. Hagan, Howard B. Demuth, “Neural Networks for Control”, Proceedings of the American Control Conference, 1999, pp. 1642-1656.
3. C. Jeyachandran and M. Rajaram, “Comparitive Performance Analysis of Various Training Algorithms for Control of CSTR Process Using Narma-L2 Control,” International Conference on Trendz in Information Sciences and Computing, 2011, pp. 5-10.
4. Hamza Chaal, “A Chemical Reactor Benchmark for Adaptive Control using V-Model and NARMA-L2 Techniques”, International Conference on Control, Automation and Systems 2007, Oct. 17-20, 2007 in COEX, Seoul, Korea, pp.2871-2875.
5. T. Procyk and E. Mamdani, "A linguistic self-organizing process controller," Automatica, vol. 15, no. I, 1979, pp. 15-30.
6. Nejaud Almalki Al-Jehani, Hazem N. Naunau and Mahamed N. Naunau, “Fuzzy Control of a CSTR Process”, International Symposium on Mechatronics and its Applications, 2012, pp. 1-6.
7. Lenka Blahova, Jan Dvoran, “Neuro-Fuzzy Control of Chemical Reactor with Disturbances”, LATEST TRENDS on SYSTEMS (Volume I), 2010, pp.336-340.
8. Glan Devadhas.G & Dr.Pushpakumar.S, “Intelligent Controller Design for a Chemical Process”, International Journal of Engineering, (IJE), vol. 4(5), pp. 399-410.
9. B. Wayne Bequette, "Process Control-Modeling Design and Simulation",Prentice Hall of India, 2003.
10. Jyh-Shing Roger Jang, “ANFIS: Adaptive-Network-Based Fuzzy Inference System”, IEEE Transactions on Systems, Man and Cybernetics, vol. 23, no. 3, May/June, 1993.
11. Hagan, M.T., Menhaj, M.B., “Training feed forward networks with the Marquardt algorithm”, IEEE Transactions on Neural Networks, vol. 5, no. 6, Nov, 1994.
12. Jang, J.-S.R.; Chuen-Tsai Sun, “Neuro Fuzzy Modelling and Control”, IEEE Proc., vol.83, pp. 378-406, March1995.
13. Neural Network Toolbox, MATLAB 2010.