

Performance Analysis of Neural Network Based Narma Control for CSTR

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Abstract

In this paper 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 response of ANFIS control is better than NARMA-L2 control.

Keywords: Adaptive Network Based Fuzzy Inference System (ANFIS), Continuous Stirred Tank Reactor (CSTR), Nonlinear Auto Regressive Moving Average (NARMA), And PID

I. INTRODUCTION

Continuous stirred tank reactor (CSTR) exhibits quite nonlinear dynamic behavior 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.

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 nonlinear 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 NARMAL2 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.

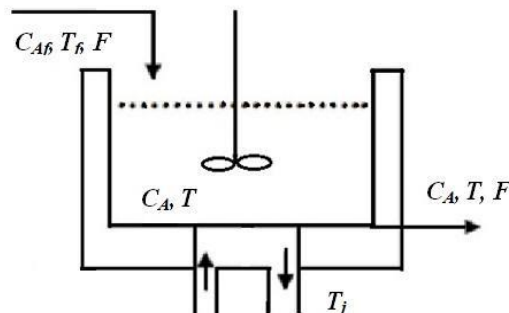


Fig. 1: Jacketed Continuous Stirred Tank Reactor Model

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.

$$V \frac{dCA}{dt} = FCaf - FCa - Vra \quad (1)$$

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

$$rA = ko(-Ea/RT)CA \quad (2)$$

Here k0 is the frequency factor, Ea 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 (Cp) and constant density (ρ) gives,

$$VpCp \frac{dT}{dt} = FpCp(Tf - T) + (-\Delta H)VrA - UA(T - Tj) \quad (3)$$

Where $-\Delta H$ is the heat of reaction, U is the heat transfer coefficient, A is the heat transfer area, Tf is the feed temperature and Tj is the jacket temperature. State Space Model obtained from (1), (2), (3) is

$$\frac{dCA}{dt} = f1(CA, T) = \frac{F}{V}(CAF - CA) - ko(-Ea/RT)CA \quad (4)$$

$$\frac{dT}{dt} = f2(CA, T) = \frac{F}{V}(Tf - T) + \frac{-\Delta H}{pcp} ko \left(-\frac{Ea}{RT} \right) CA - \frac{UA}{Vpcp}(T - Tj) \quad (5)$$

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.

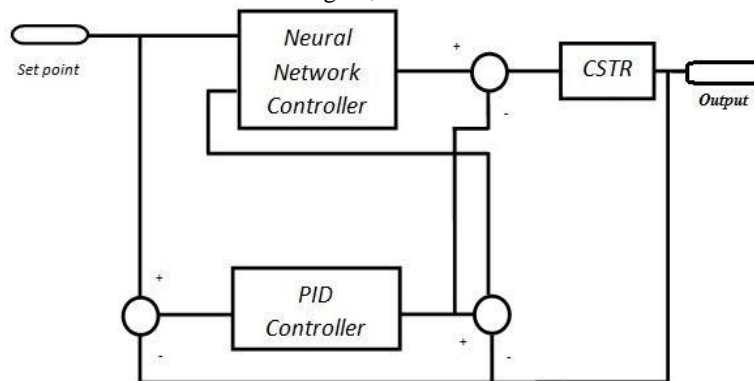


Fig. 2: PID Based NARMA-L2 Control Structure

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.

B. 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]

$$G1(s) = [P + I \left(\frac{1}{s} \right) + D \left(\frac{Ns}{s} + N \right)] \quad (6)$$

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.

C. 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].

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

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.

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

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.

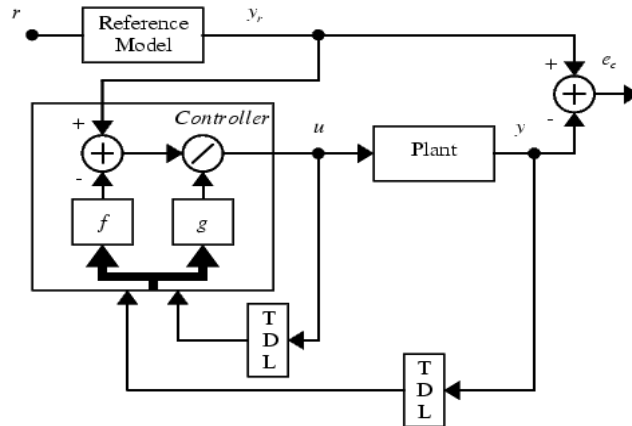


Fig.3: Block Diagram of NARMA-L2 Controller

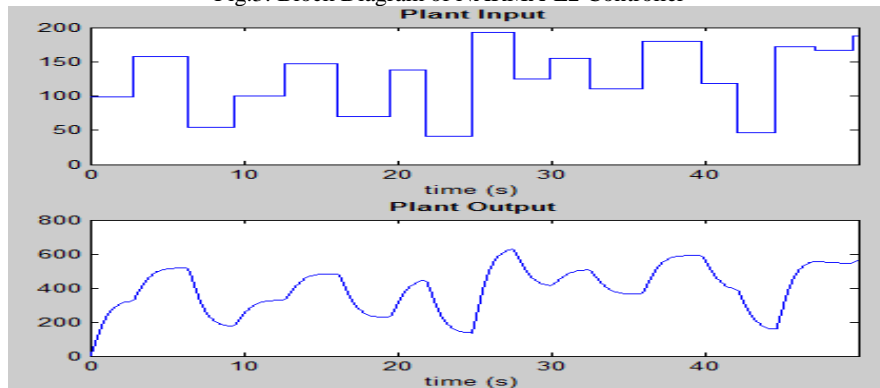


Fig. 4: Training Data Plot for NARMA-L2 Controller

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 backpropagation 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.

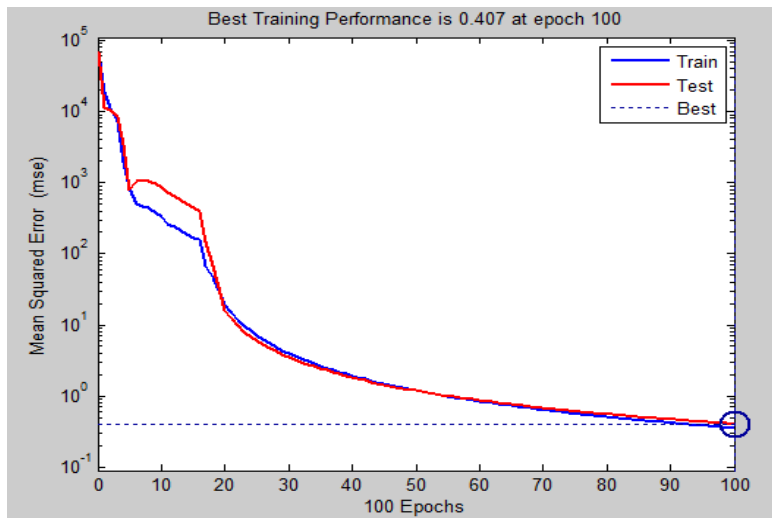


Fig. 5: Mean Square Error of the Training

D. 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.

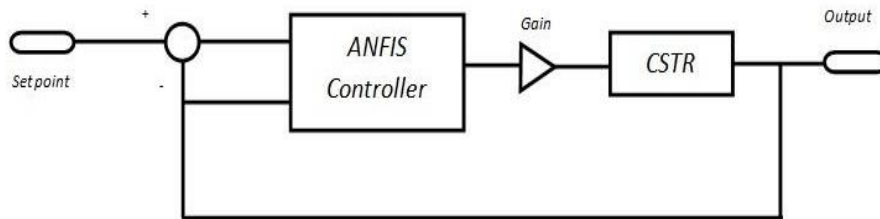


Fig. 6: ANFIS Control Structure

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.

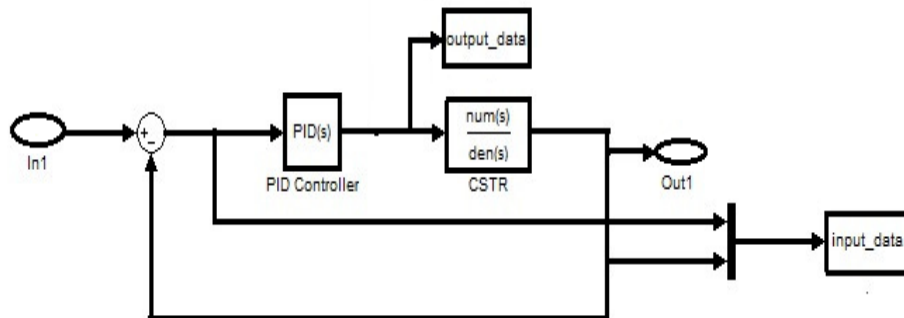


Fig. 7: PID Control Structure

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.

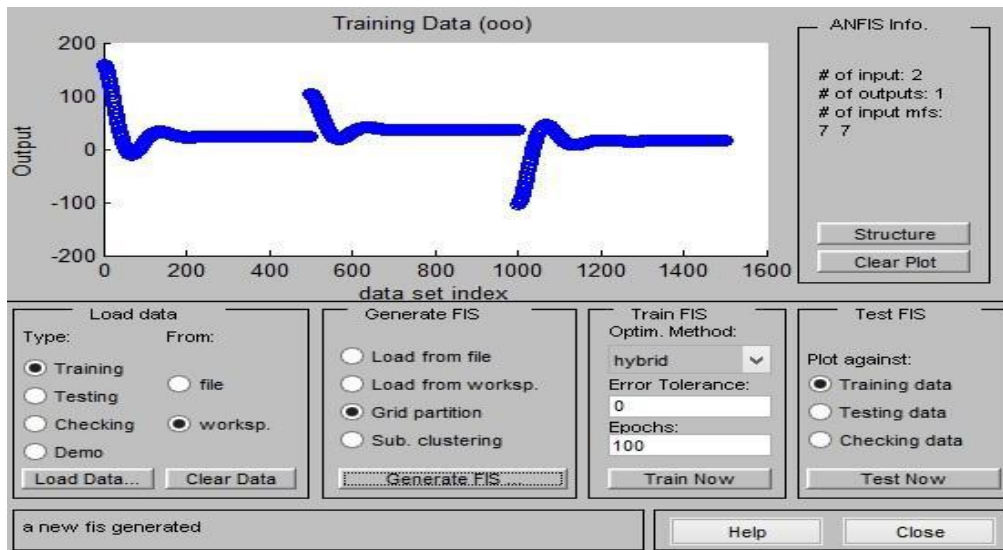


Fig. 8: Training Data Plot in Anfiseditor

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.

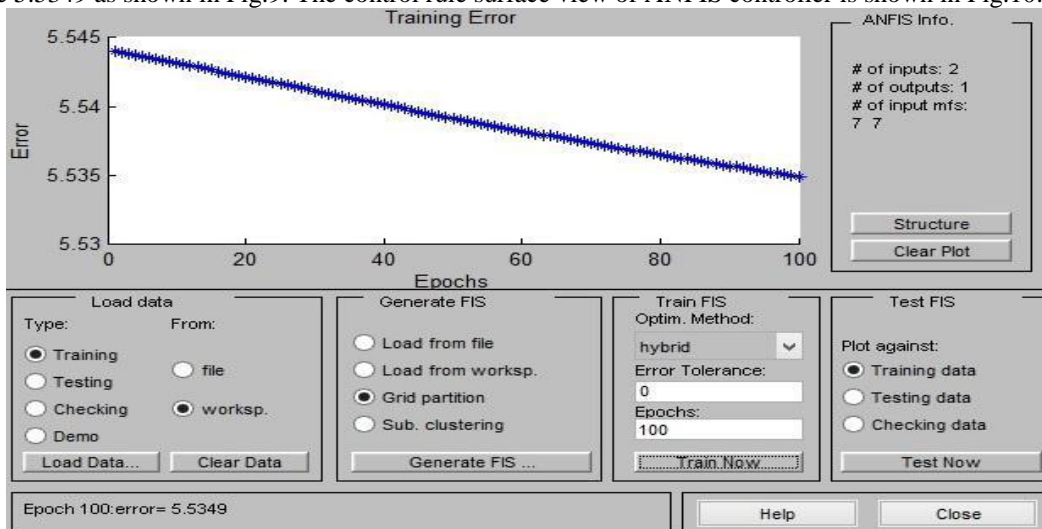


Fig. 9: Training Error Plot and Training Error

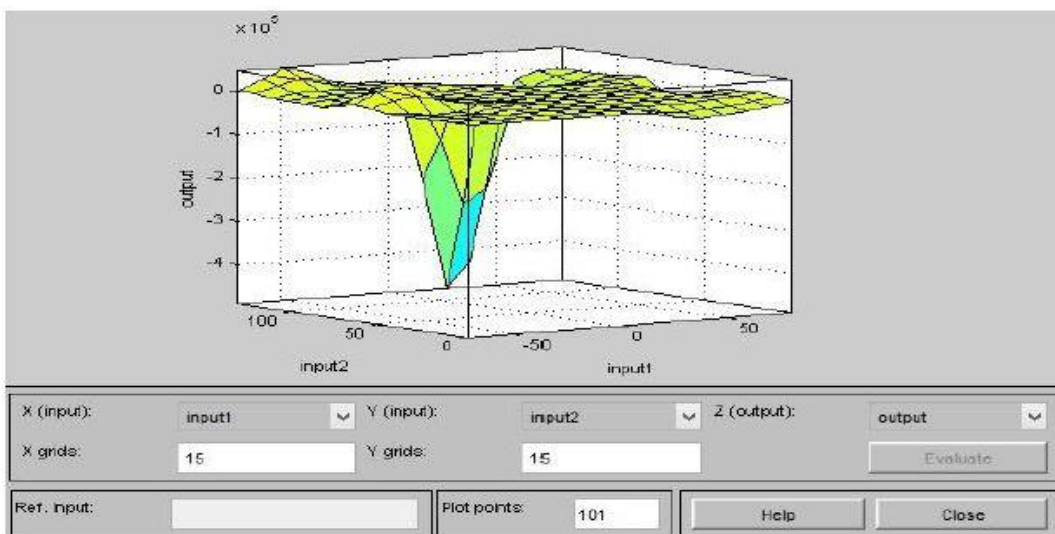


Fig. 10: Control Surface Rule View of ANFIS

III. 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 are shown in Fig. 11. The time domain specifications for temperature regulation in CSTR equipped with the proposed controllers are specified in TABLE 1

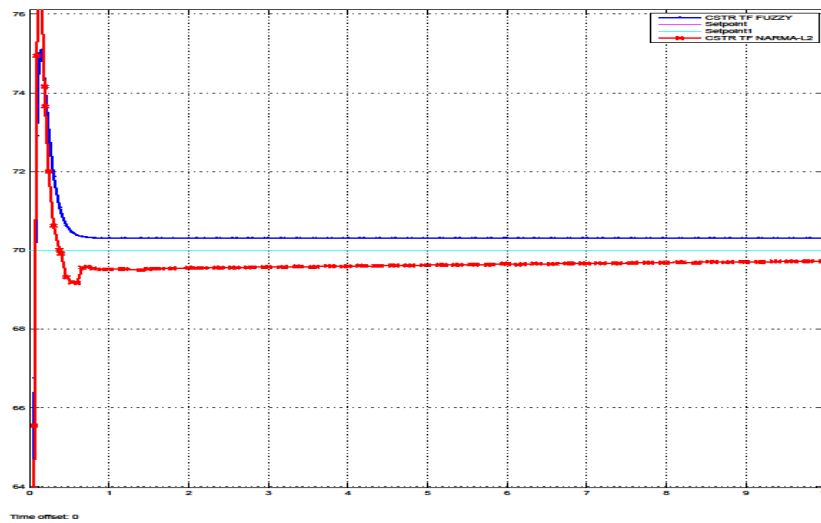


Fig .11: Time Response of NARMA-L2 and ANFIS Control

Table- I

<i>Timedomain Specification</i>	<i>ANFIS Controller</i>	<i>NARMA-L2 Controller</i>
<i>Settling Time</i>	<i>1.9%</i>	<i>2.2%</i>
<i>Overshoot %</i>	<i>17.5%</i>	<i>19.6%</i>
<i>Steady State Error Ess</i>	<i>0.3</i>	<i>0.7</i>

Summary of the Performance Characteristics

Furthermore the reference tracking capability of the proposed controllers for varying set point temperature in CSTR is shown in Fig.11

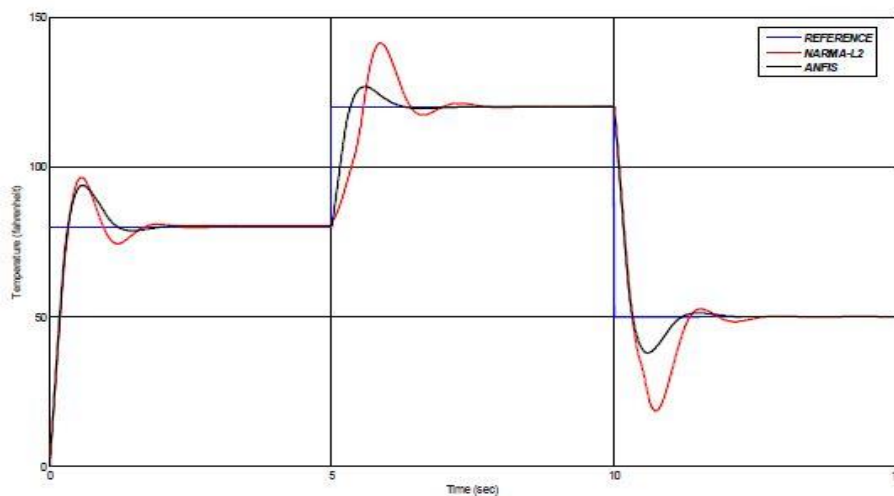


Fig. 12: Reference Tracking Performance of NARMA-L2 and ANFIS Control

IV. 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 NARMAL2 control. Thus the T-S Fuzzy technique is useful in control of nonlinear system. Afterwards ANFIS

which is combination of Neural Network and Fuzzy inference system is more useful method for controlling such nonlinear system.

ACKNOWLEDGMENT

We would like to express our gratitude towards our guide and mentor Prof. A.B. PATIL 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.

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