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Temperature Control System Using ANFIS

T.P.Mote, Dr.S.D.Lokhande

Abstract - This paper describes three important aspects: design, simulation and Implementation of Adaptive Neuro fuzzy system applied to the temperature variable of a thermal system with a range of 25^0C to 50^0C.An Adaptive Neuro Fuzzy Inference System (ANFIS) based controller is proposed for water temperature control. The generation of membership function is a challenging problem for fuzzy sytems and the response of fuzzy systems depends mainly on the membership functions. The ANFIS based input – output model is used to tune the membership functions in fuzzy system. Experimental results are compared with the conventional PID Controller and Neural Network Controller. All the controllers are tested in various operating conditions and varying set point changes and also for disturbance rejection. This shows that better performance can be achieved with ANFIS tuning.

Index Terms — ANFIS, Artificial neural network, PID, Temperature control.

I. INTRODUCTION

Process control systems are often nonlinear and difficult to control accurately. Their dynamic models are more difficult to derive than those used in aerospace or robotic control, and they tend to change in an unpredictable way.

The conventional PID controllers, in various combinations have been widely used for industrial processes due to their simplicity and effectiveness for linear systems, especially for first and second order systems. It has been well known that Proportional Integral Derivative (PID) controllers can be effectively used for linear systems, but usually cannot be used for higher order and nonlinear systems [8].

This paper addresses an application that involves the temperature control system. It presents a fuzzy controller that uses an adaptive neuro-fuzzy inference system. Artificial Neural Network (ANN) learns from scratch by adjusting the interconnections between layers. Fuzzy Inference system (FIS) is a popular computing framework based on the concept of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. A neuro-fuzzy system is simply a fuzzy inference system trained by a neural network learning algorithm.

II. LITERATURE SURVEY

Fuzzy systems have the ability to represent comprehensive linguistic knowledge: given for example by a human expert and perform reasoning by means of rules. However, fuzzy systems do not provide a mechanism to automatically acquire or tune those rules. On the other hand neural-networks are adaptive systems that can be trained and tuned from a set of samples. Once they are trained, neural-networks can deal with new input data by generalizing the acquired knowledge. Nevertheless, it is very difficult to extract and understand that knowledge. In other words, fuzzy systems and neural-networks are complementary paradigms [1].

The fuzzy logic controllers and the neural networks (both static and dynamic) are two modern system analyses which had been applied successfully in many practical applications .These two techniques are very useful when the system under study is partially unknown and previously assumed to be nonlinear. The combination between the two methods (Neuro-fuzzy control systems) is a powerful identification and control technique [2].

In recent years, Fuzzy Inference Systems (FISs) and Artificial Neural Networks (ANNs) have attracted considerable attention as candidates for novel computational systems because of the variety of the advantages that they offer over conventional computational systems. Unlike other classical control methods, Fuzzy Logic Control (FLC) and ANNs are more model free controllers, i.e. they do not require exact mathematical model of the system [3].

For non-linear modeling, neural networks and neuro-fuzzy modeling approaches have received a great deal of attention. The drawbacks are the complexity and the darkness of their structures, especially, in modeling complex nonlinear systems. It has been shown that many types of nonlinearities in industry processes are effectively modeled with hybrid models, like heating and cooling processes, fermentation, solid drying processes, continuous stirred tank reactor (CSTR) [4].

The temperature system has non linearity, long delay time, and large time constant and undetermined system. At present Industries uses the PID technique for temperature control. PID control is a crisp control, the self tuning of the P, I, D parameters are quite difficult and the resultant control is with overshoot and with large time constants [1]. Fuzzy logic used to express uncertainty in an expert system. The problem of Fuzzy controller is reduced to acquisition of a correct set of IF-THEN rules that can be obtained by human expert. ANFIS controller is the combination of fuzzy logic and ANN and capable to generate expert systems by itself. [5].

The fixed gain feedback controllers (PID) are insufficient to compensate for parameter variations in the plant as well **as** to adopt to changes in the process environment. The Advent of Fuzzy Logic Control (FLC) has inspired new resources for more efficient control. It does not require a ***priori*** model of the process for implementation. In the traditional FLC the optimal membership values are found by trial and error which is laborious. Also the

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T.P.Mote is Lecturer in E&TC with Sinhgad Technical Education Society's Sou. Venutai Chavan Polytechnic, Pune-411041, and Maharashtra, India. E-mail: tanujam79@gmail.com

Dr.S.D.Lokhande is Professor in E&Tc Department in Sinhgad Technical Education Society's Sinhgad College of Engineering, Pune-411041, and Maharashtra, India. E-mail: l_shashikant@yahoo.co.in

conventional method of transferring the range of input variables into corresponding universe of discourse is time consuming. The transfer of the range of input variables into corresponding universe of discourse can be carried out using Artificial Neural Networks [6].

The applications of neural networks to control systems have become increasingly important. The backpropagation neural network based on the generalized delta learning rule, a gradient descent search technique, has been widely used. The backpropagation algorithm has several disadvantages, among which is lack of guaranteed convergence, but it's simple yet powerful mathematical algorithm has made it the mainstay of neuro-computing. Before the neural network can be used as a controller, it first must learn the model of the plant. There are several learning architectures proposed whereby the neural network may be trained [7].

III. SYSTEM OVERVIEW

A simple and versatile way is proposed to achieve controlled temperature using an Adaptive Neuro Fuzzy Controller. The system used as a temperature controller is shown in figure 1. A small water tank with the capacity of 6 liters water is used. It consists of a heater coil at the mouth of water inlet. Temperature sensor is inserted outside water tank near the outlet. Signal conditioner is used to transfer sensed signal to the computer via microcontroller. The microcontroller sends the sensed temperature to the computer where the ANFIS Controller and other controllers are used. Here RS-232 interface is used for communication between the hardware and the controllers. The controller in the computer then gives out a control signal to the microcontroller depending on the error. This control signal is used by the microcontroller to generate the pulse width modulated (PWM) which is given to the heater through TRIAC and opto-isolator. The ac signal output from TRIAC then drives the heater. Neuro –Fuzzy controller is used for temperature control. The temperature results are also displayed on LCD display. The bulb connected in parallel to the heater indicates the on/off condition of the heater as well as the PWM sent to the heater.

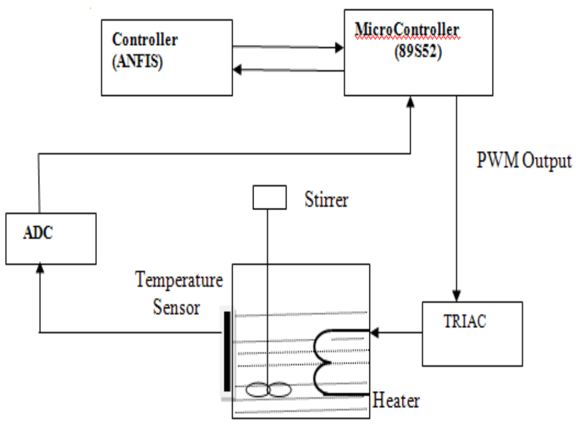

Fig 1: Block Diagram of proposed system

A.Adaptive Neuro Fuzzy System (Anfis)

ANFIS is a network which uses learning capability of neural network to enhance the performance of the system using priori knowledge.

Let us assume the fuzzy inference system with two inputs x and y and one output. Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno's type as given below:

If x is A1 and y is B1, then $f1 = p1x + q1y + r1$

If x is A2 and y is B2, then $f2 = p2x + q2y + r2$ then the fuzzy reasoning is illustrated in Fig 2, and the corresponding equivalent ANFIS architecture is shown in Fig 5.3b.The node functions in the same layer are of the same function family as described below:

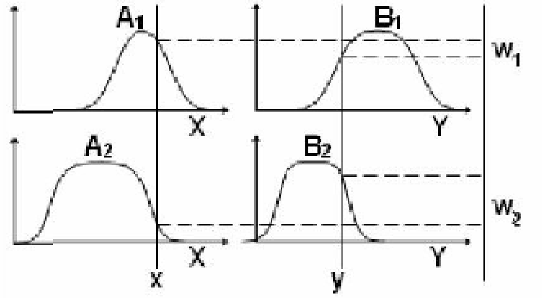

Fig. 2: ANFIS reasoning showing firing rules of different membership functions for TSK Model

Layer 1: Every node i in this layer is a square node with a node function $Oi^1 = \mu_{Ai}(x)$ where x is the

$$f1 = p1x + q1y + r1$$

$$f2 = p2x + q2y + r2 \quad \Rightarrow \frac{\omega 1 f1 + \omega 2 f2}{\omega 1 + \omega 2}$$

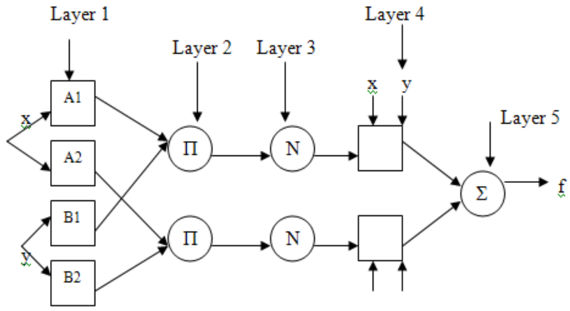

Fig 3: ANFIS structure for 2 –input variables for TSK Model

input to node 0, and A is the linguistic label associated with this node function. In other words, μ is the membership function of A, and it specifies the degree to which the given x satisfies the quantifier Ai. Gaussian Membership function is chosen with maximum equal to 1 and minimum equal to 0. Parameters in this layer are referred to as the premise parameters.Membership functions are used for each of the input in this layer.

Layer 2: Every node in this layer is a circle node labeled H, which multiplies the incoming signals and sends the product out. For instance,

$\omega = \mu_{Ai}(x) * \mu_{Bi}(y)$; i=1, 2

Each node output represents the firing strength of a rule.

Layer 3: Every node in this layer is a circle node labeled N. The i-th node calculates the ratio of the i-th rule's firing strength to the sum of all rules' firing strengths:

$\overline{\omega}_i = \dfrac{\omega 1}{\omega 1+\omega 2}$; i=1,2 For convenience, outputs of this layer will be called normalized firing strengths.

Layer 4: Every node 1 in this layer is a square node with a node function

$$O^4 i = \overline{\omega}_i f_i = \omega_i (pix + qiy + ri)$$

where, $\overline{\omega}_i$ is the output of layer 3 and {pi, qi, ri} is the parameter set. Parameters in this layer will be referred to as consequent parameters.

Layer 5: The single node in this layer is a circle node labeled E that computes the overall output as the summation of all incoming, signals, i.e.

$$O^5 i = \text{Overall output} = \sum \overline{\omega i}\, fi = \frac{\sum \omega i fi}{\sum ifi}$$

Table 1: MSE for Different Controllers

Type of Controller	MSE
ANFIS with Trapezoidal	0.5000
ANFIS with Gaussian	2.0000
ANFIS with Triangular	0.5000
Neural Network	2.0000
PID	18.0000

IV RESULTS

A. Mean Squared Error Performance

The Controller was tested with setpoint 65 i.e. temp 32.5deg with initial temp around 27 degrees and for 500 iterations. The results were compared with conventional PID and Neural Network controller.

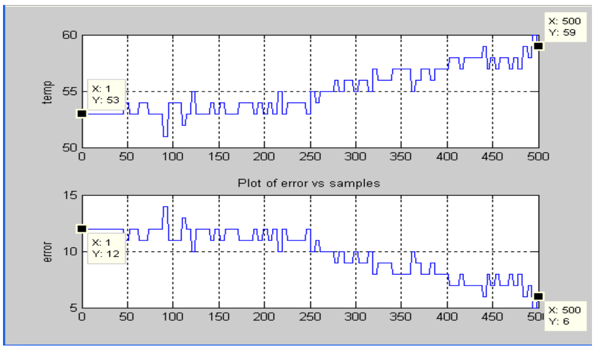

Fig 4: Response of PID for setpoint of 65.

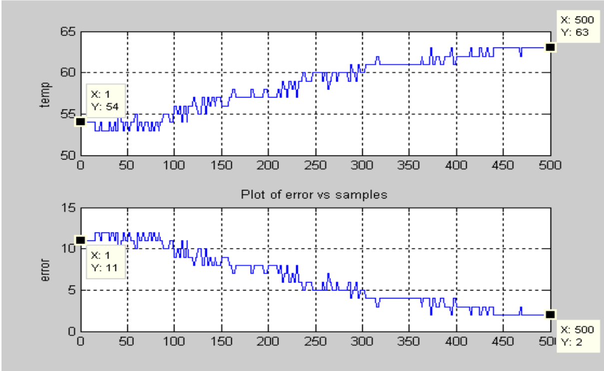

Fig 5: Response of Neural Network for setpoint of 65.

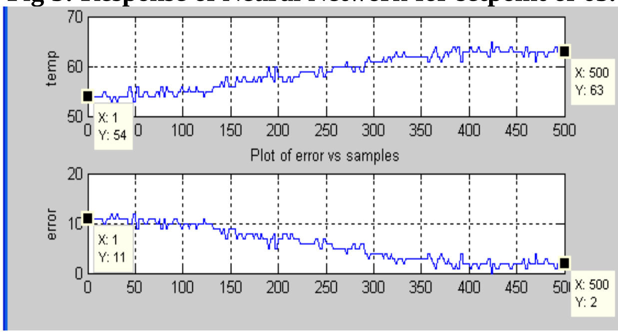

Fig 6: Response of ANFIS with Gaussian membership function for setpoint of 65.

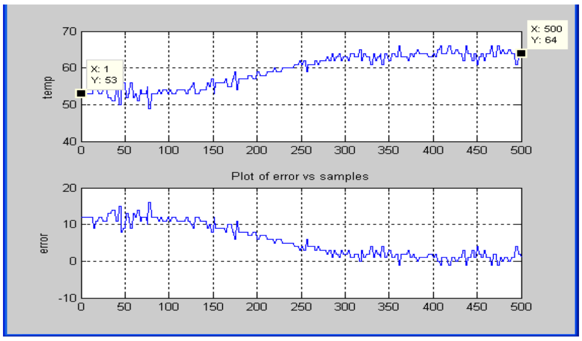

Fig 7: Response of ANFIS with triangular membership function for setpoint of 65.

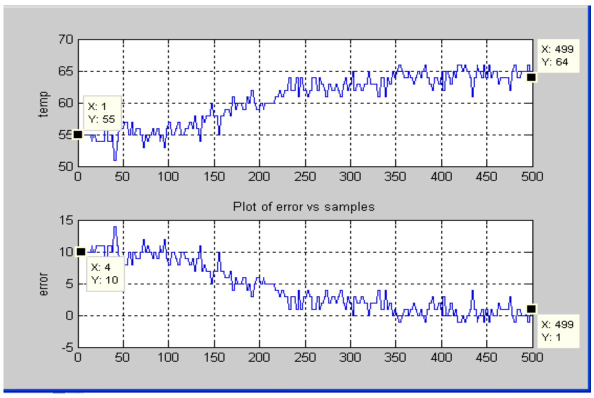

Fig 8: Response of ANFIS with trapezoidal membership function for setpoint of 65.

B. Setpoints Tracking

The controllers were also tested for different setpoint 55, 60, 70 with 300,350, 550 iterations & initial temp around 25 degrees.

Results obtained with ANFIS system are more

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satisfactory than Neural and PID Controller.

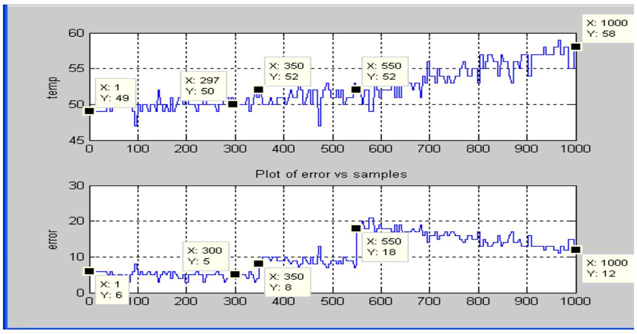

Fig 9: Response of PID for setpoint tracking.

Table 2: Results of MSE of all Controllers for setpoint Tracking

Type of Controller	MSE
ANFIS with Trapezoidal	0.5000
ANFIS with Gaussian	2.0000
ANFIS with Triangular	2.0000
Neural Network	18.000
PID	72.0000

The table 2 shows the performance of all the controllers for various setpoint of 55, 60, and 70.

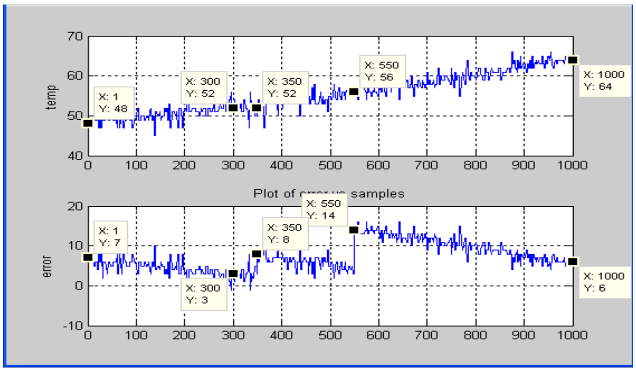

Fig 10: Response of Neural Network for setpoint tracking.

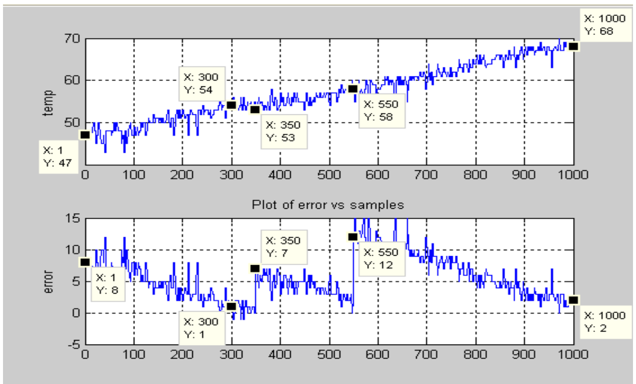

Fig 11: Response of ANFIS Gaussian membership function for setpoint tracking.

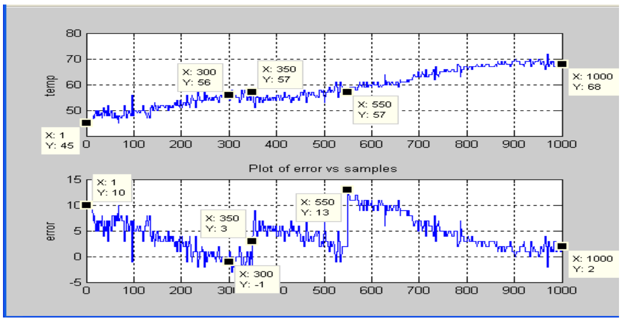

Fig 12: Response of ANFIS triangular membership function for setpoint tracking .

From the above results it is clear that ANFIS reached to 68 i.e. it almost reached to the last setpoint of 70. Neural network tried to reach but still lagged behind ANFIS, it reached to 64. Whereas PID was not at all able to track the setpoint.PID reached only to 58.Thus ANFIS results are 15% better than PID and 5% better than Neural network.

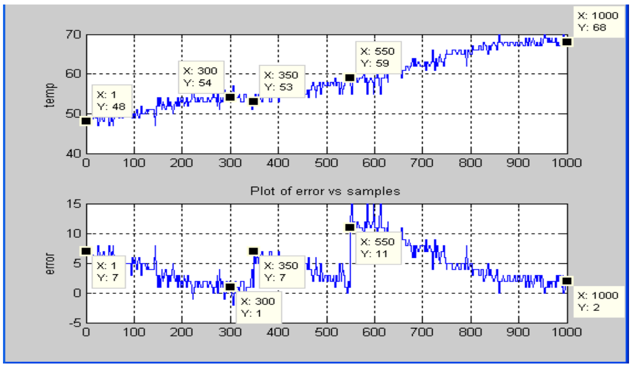

Fig 13: Response of ANFIS Trapezoidal membership function for setpoint tracking.

C. Disturbance Rejection

The water was heated for setpoint of 88 i.e. 44 degrees temperature starting with initial temperature of around 34 degrees .The cold water was put in the middle at 500th iteration during the heating process.Here also ANFIS showed good results.

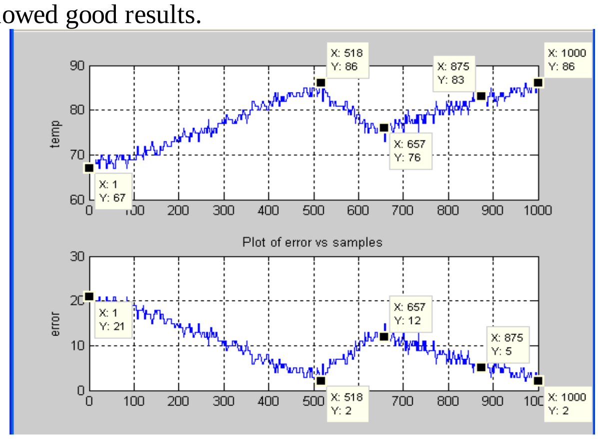

Fig 14: Response of ANFIS Gaussian membership function for disturbance rejection

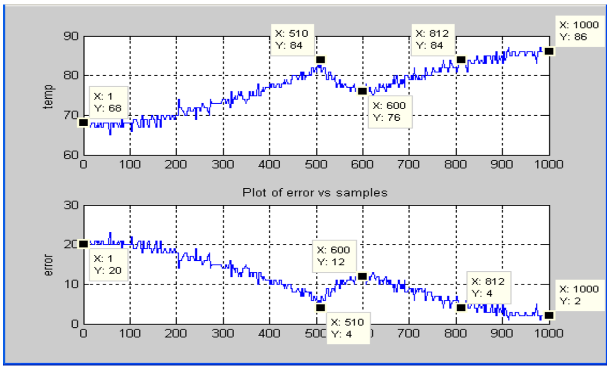

Fig 15: Response of ANFIS Trapezoidal membership function for disturbance rejection

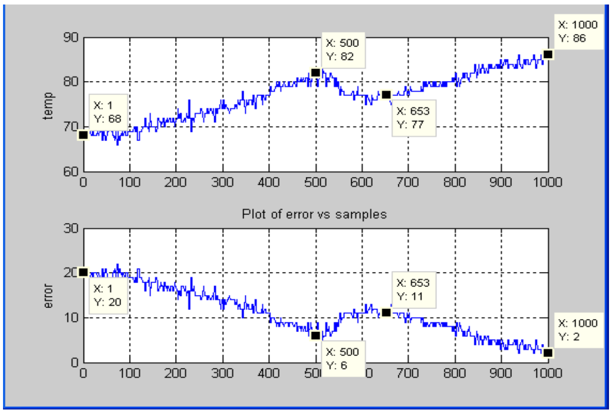

Fig 16: Response of ANFIS Triangular membership function for disturbance rejection

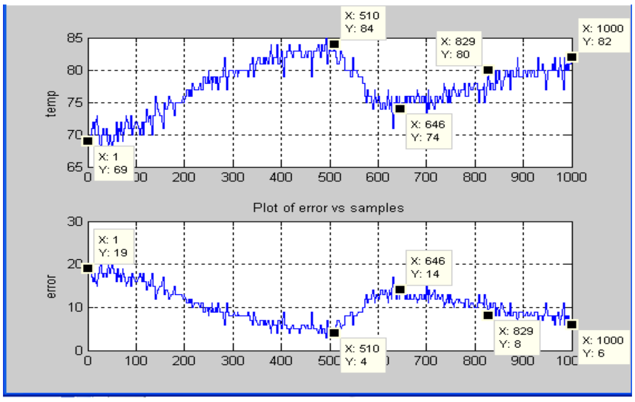

Fig 17: Response of Neural Network for disturbance rejection

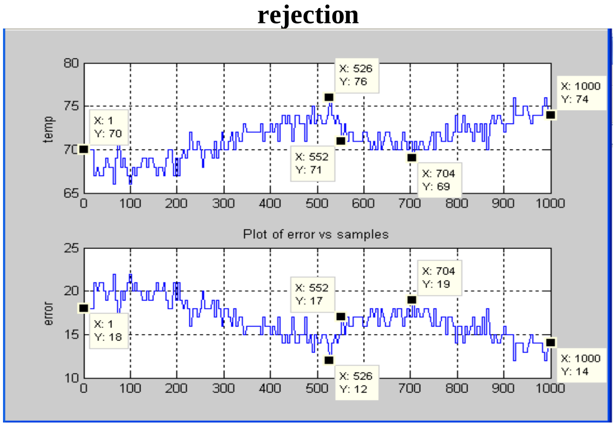

Fig 18: Response of PID for disturbance rejection .

Table 3: Results of MSE of all Controllers for Disturbance rejection

Type of Controller	MSE
ANFIS with Trapezoidal	2.0000
ANFIS with Gaussian	2.0000
ANFIS with Triangular	2.0000
Neural Network	18.000
PID	42.0000

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The table 3 shown indicates the mean squared error performance of all the three controllers for disturbance rejection.

V. CONCLUSION

ANFIS based controller is compared with Neural network controller and PID Controller for single set point, varying setpoint changes, as well as disturbance rejection and its mean squared error is calculated. Thus it is seen from the above results that ANFIS worked well in all the situations. Mean squared error obtained for both neural network as well as ANFIS with Gaussian membership function is same for a single set point but mse is reduced for triangular and trapezoidal membership functions. The mse results obtained for setpoint tracking and disturbance rejection of ANFIS are almost 15% better than PID and 5% better than neural network.PID showed poor performance in all the three situations. Thus with ANFIS tuning, better performance is achieved.

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AUTHOR PROFILE

First Author Mrs.T.P.Mote. She has completed degree in the field of Electronics and Telecommunications in the year 2000 from Pune University, She is presently pursuing M.E. in Digital Electronics at Sinhgad College of Engineering affiliated to Pune University. She is presently working

as a Lecturer in STES's Sou.Venutai Chavan Polytechnic, E&Tc Department. She has published 1 paper in International Conference and 2 National Conferences.

Mrs. Mote is a Life member of ISTE,New Delhi and Associate member of IETE,New Delhi.

Second Author Dr. S. D. Lokhande was born on September 27, 1967. He completed his BE in Electronics Engineering in 1985 from Marathwada University, Aurangabad. He completed ME and received PhD in Electronics Engineering, from Shivaji University, Kolhapur, in 1996 and 2006 respectively. His research interests are in Artificial Neural Network and Image Processing.

He has 21 years of teaching experience and presently working as Professor in E & TC department at Sinhgad College of Engineering, Pune.

He is life member of ISTE, IEEE, New Delhi and ISOI, Bangalore. Dr. Lokhande is also a fellow of IETE, New Delhi.