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Artificial Neural Network Based Model Reference Adaptive Control for a Second Order System.

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ABSTRACT: In this paper a Artificial Neural Network (ANN) approach for model reference adaptive control (MRAC) scheme for MIT rule in presence of first order and second order noise has been discussed. This noise has been applied to the second order system. Simulation is done in MATLAB-Simulink and the results are compared for varying adaptation mechanisms due to variation in adaptation gain with and without noise. The result shows that system is stable.

Keywords: Adaptive Control, MRAC (Model Reference Adaptive Controller), Adaptation Gain, MIT rule, Neural Network, Artificial Neural Network, ANN, Nonlinear, Noise.

I. INTRODUCTION.

Robustness in Model reference adaptive Scheme is established for bounded disturbance and unmodeled dynamics. Adaptive controller without having robustness property may go unstable in the presence of bounded disturbance and unmodeled dynamics. Artificial Neural Network based adaptive controller gives the better response even in the present of bounded disturbance and unmodeled dynamics.

Model reference adaptive controller has been designed to control the nonlinear system. MRAC forces the plant to follow the reference model irrespective of plant parameter variations to decrease the error between reference model and plant to zero[2]. Effect of adaption gain on system performance for MRAC using MIT rule for first order system [3] and for second order system[4] has been discussed. Comparison of performance using MIT rule & and Lyapunov rule for second order system for different value of adaptation gain is discussed [1]. Even in the presence of bounded disturbance and unmodeled dynamics system show stability in chosen range of adaptation gain[5].

Now a days, Artificial Neural Network (ANN) is used for nonlinear, higher order and time delay system because their ability handle complex input output mapping without analytical model of system [6]. Artificial Neural Network (ANN) controller gives the controlled input to non linear plant of MRAC without disturbances has been discussed [7].

In this paper adaptive controller for second order system using MIT rule in the presence of first order and second order bounded disturbance and unmodeled dynamics has been discussed first and then Artificial Neural Network has been applied. Simulation has been done for different value of adaptation gain in MATLAB with Artificial Neural Network and without Artificial Neural Network (ANN) and accordingly performance analysis has been discussed for MIT rule for second order system in the presence of bounded disturbance and unmodeled dynamics.

II. MODEL REFERENCE ADAPTIVE CONTROL

Model reference adaptive controller is shown in Fig. 1. The basic principle of this adaptive controller is to build a reference model that specifies the desired output of the controller, and then the adaptation law adjusts the unknown parameters of the plant so that the tracking error converges to zero [6]

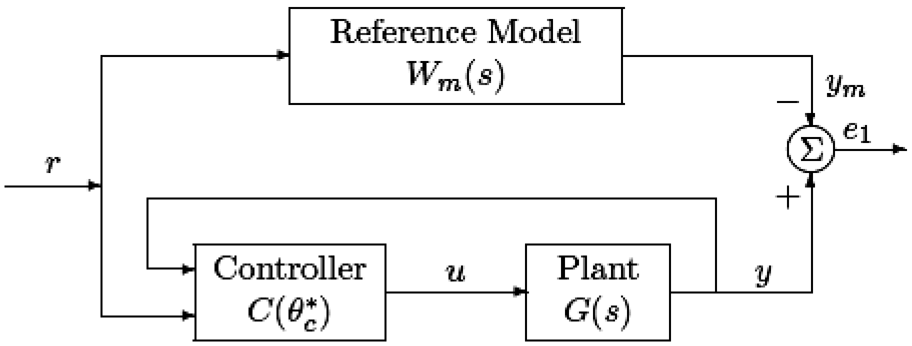

Figure. 1

III. MIT RULE

There are different methods for designing such controller. While designing an MRAC using the MIT rule, the reference model, the controller structure and the tuning gains for the adjustment mechanism is selected. MRAC begins by defining the tracking error, e, which is difference between the plant output and the reference model output:

system model e=y(p) −y(m) (1)

The cost function or loss function is defined as
F (θ) = e^2 / 2 (2)

The parameter θ is adjusted in such a way that the loss function is minimized. Therefore, it is reasonable to change the parameter in the direction of the negative gradient of F, i.e

$$J(\theta) = \frac{1}{2} e^2(\theta) \quad (3)$$

$$\frac{d\theta}{dt} = -\gamma \frac{\delta J}{\delta \theta} = -\gamma e \frac{\delta e}{\delta \theta} \quad (4)$$

– Change in γ is proportional to negative gradient of J

$$J(\theta) = |e(\theta)|$$

$$\frac{d\theta}{dt} = -\gamma \frac{\delta e}{\delta \theta} sign(e) \quad (5)$$

$$\text{where} \quad sign(e) = \begin{cases} 1, & e > 0 \\ 0, & e = 0 \\ -1, & e < 0 \end{cases}$$

From cost function and MIT rule, control law can be designed.

IV. MATHEMATICAL MODELLING IN PRESENCE OF BOUNDED AND UNMODELED DYNAMICS.

Model Reference Adaptive Control Scheme is applied to a second order system using MIT rule has been discussed [3] [4]. It is a well known fact that an under damped second order system is oscillatory in nature. If oscillations are not decaying in a limited time period, they may cause system instability. So, for stable operation, maximum overshoot must be as low as possible (ideally zero).

In this section mathematical modeling of model reference adaptive control (MRAC) scheme for

MIT rule in presence of first order and second order noise has been discussed

Considering a Plant: $\ddot{y}_p$ = -a$\dot{y}_p$ - by + bu (6)

Consider the first order disturbance is $\dot{y}_d$= -$y_d k$ + $u_d k$

Where y_p is the output of plant (second order under damped system) and u is the controller output or manipulated variable.

Similarly the reference model is described by:

$$\ddot{y}_m = -a_m \dot{y}_m - b_m y + b_m r \qquad (7)$$

Where y_m is the output of reference model (second order critically damped system) and r is the reference input (unit step input).

Let the controller be described by the law:

$$u = \theta_1 r - \theta_2 y_p \qquad (8)$$

$$e = y_p - y_m = G_p G_d u - G_m r \, (9)$$

$$y_p = G_p G_d u = \left(\frac{b}{s^2 + as + b}\right)\left(\frac{k}{s+k}\right)(\theta_1 r - \theta_2 y_p)$$

$$y_p = \frac{bk\theta_1}{(s^2 + as + b)(s+k) + bk\theta_2} r$$

$$e = \frac{bk\theta_1}{(s^2 + as + b)(s+k) + bk\theta_2} r - G_m r$$

$$\frac{\partial e}{\partial \theta_1} = \frac{bk}{(s^2 + as + b)(s+k) + bk\theta_2} r$$

$$\frac{\partial e}{\partial \theta_2} = -\frac{b^2 k^2 \theta_1}{[(s^2 + as + b)(s+k) + bk\theta_2]^2} r$$

$$= -\frac{bk}{(s^2 + as + b)(s+k) + bk\theta_2} y_p$$

If reference model is close to plant, can approximate:

$$(s^2 + as + b)(s+k) + bk\theta_2 \approx s^2 + a_m s + b_m$$

$$bk \approx b \qquad (10)$$

$$\frac{\partial e}{\partial \theta_1} = b / b_m \frac{b_m}{s^2 + a_m s + b_m} u_c$$

$$\frac{\partial e}{\partial \theta_2} = -b / b_m \frac{b_m}{s^2 + a_m s + b_m} y_{plant} \qquad (11)$$

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Controller parameter are chosen as $\theta_1 = b_m$/b and $\theta_2 = (b - b_m)$/b

Using MIT

$$\frac{d\theta_1}{dt} = -\gamma \frac{\partial e}{\partial \theta_1} e = -\gamma \left(\frac{b_m}{s^2 + a_m s + b_m} u_c \right) e \qquad (12)$$

$$\frac{d\theta_2}{dt} = -\gamma \frac{\partial e}{\partial \theta_2} e = \gamma \left(\frac{b_m}{s^2 + a_m s + b_m} y_{plant} \right) e \qquad (13)$$

Where $\gamma = \gamma' \text{x}\, b / b_m$ = Adaption gain

Considering a =10, b = 25 and a_m =10 , b_m = 1250

V. MIT RULE IN PRESENT OF BOUNDED DISTRUBANCE AND UNMODELED DYNAMICS:

Consider the first order disturbance:

$$G_d = \frac{1}{s+1}$$

Time response for different value of adaption gain for MIT rule in presence of first order disturbance is given below:

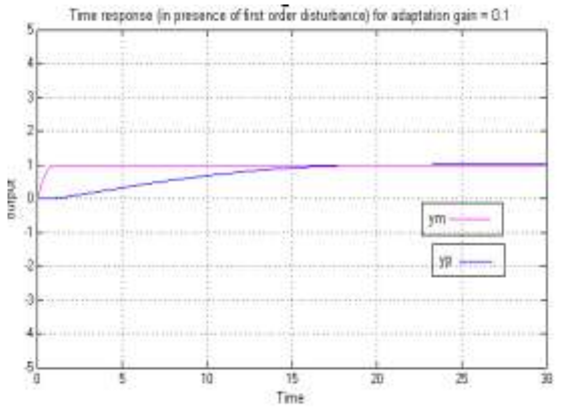

Figure 2

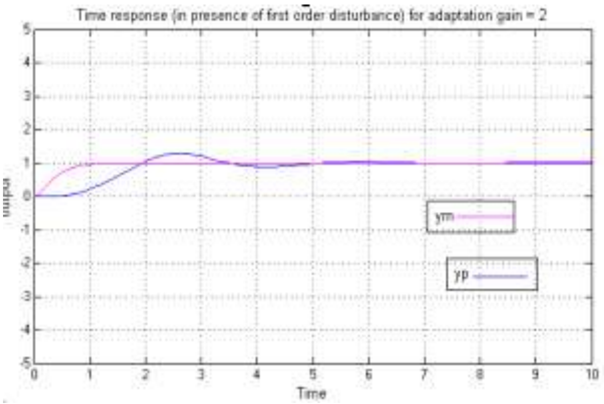

Figure 3

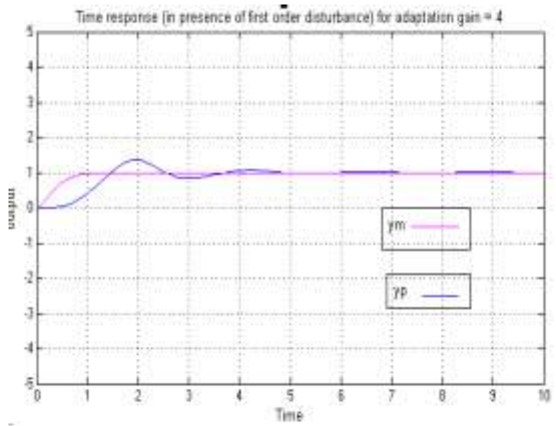

Figure 4

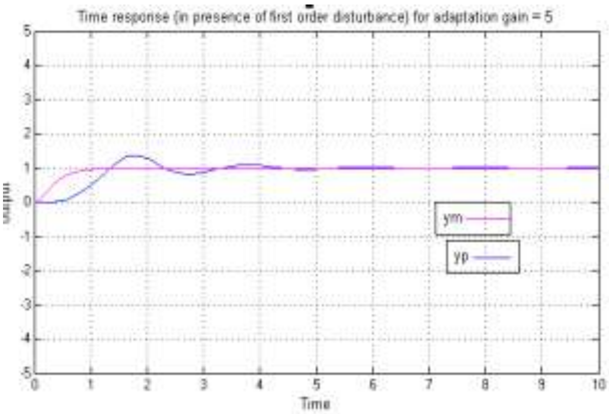

Figure 5

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Simulation results with different value of adaptation gain for MIT rule in presence of first order bounded and unmodeled dynamics is summarized below:

	Without any controller	In presence of first order bounded and unmodeled dynamics			
		γ =0.1	γ =2	γ =4	γ =5
Maximum Overshoot (%)	61%	0	27%	30%	35%
Undershoot (%)	40%	0	15%	18%	21%
Settling Time (second)	1.5	26	8	6	4

In the presence of first order disturbance the adaptation gain increases the overshoot and undershoot with decrease in settling time. This overshoot and undershoot are due to the first order bounded and unmodeled dynamics. It shows that even in the presence of first order bounded and unmodeled dynamics, system is stable. Consider the second order disturbance:

$$G_d = \frac{25}{s^2 + 30s + 25}$$

Time response for different value of adaption gain for MIT rule in presence of first order disturbance is given below:

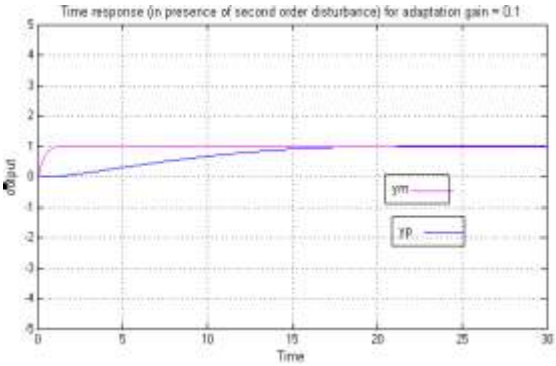

Figure 6

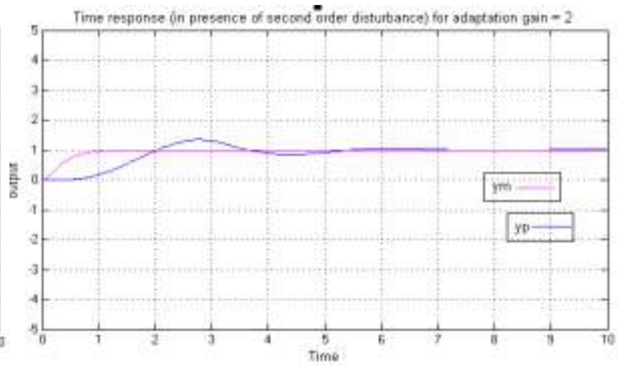

Figure 7

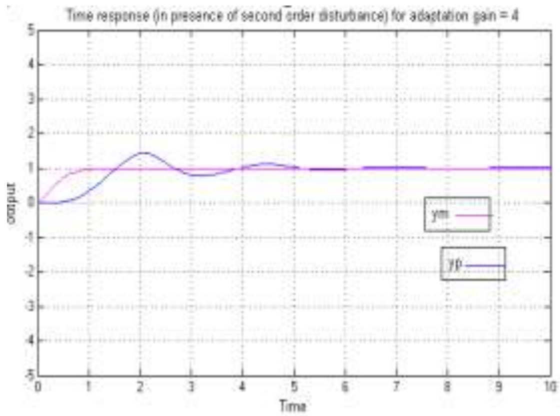

Figure 8

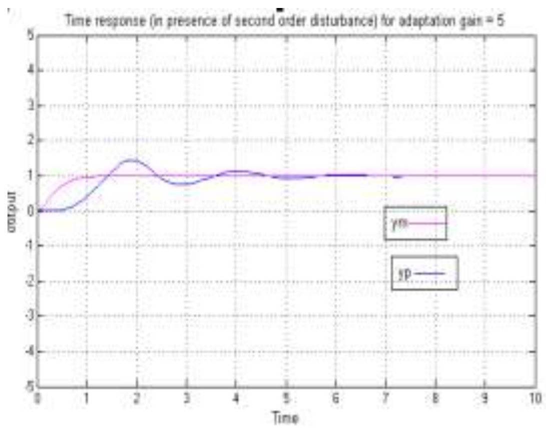

Figure 9

Simulation results with different value of adaptation gain for MIT rule in presence of second order bounded and unmodeled dynamics is summarized below:

	Without any controller	In presence of second order bounded and unmodeled dynamics			
		γ =0.1	γ =2	γ =4	γ =5
Maximum Overshoot (%)	61%	0	35%	40%	45%
Undershoot (%)	40%	0	10%	15%	20%
Settling Time (second)	1.5	30	12	10	7

In the presence of first order disturbance the adaptation gain increase the overshoot and undershoot with decrease in settling time. This overshoot and undershoot are due to the second order bounded and unmodeled dynamics. It shows that even in the presence of first order bounded and unmodeled dynamics, system is stable.

VI. ARTIFICIAL NEURAL NETWORK:

Artificial neural networks, usually simply called neural networks, are computing systems vaguely inspired by the biological neural networks that constitute animal brains Neural Network is computational device, which is basically a computer model of brain. The main objective is to develop a system to perform various computational tasks faster than the traditional systems. An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain.

6. 1 BIOLOGICAL NEURON:

A biological neural network is composed of a groups of chemically connected or functionally associated neurons. A single neuron may be connected to many other neurons and the total number of neurons and connections in a network may be extensive. Basic of biological neuron is shown in figure 10

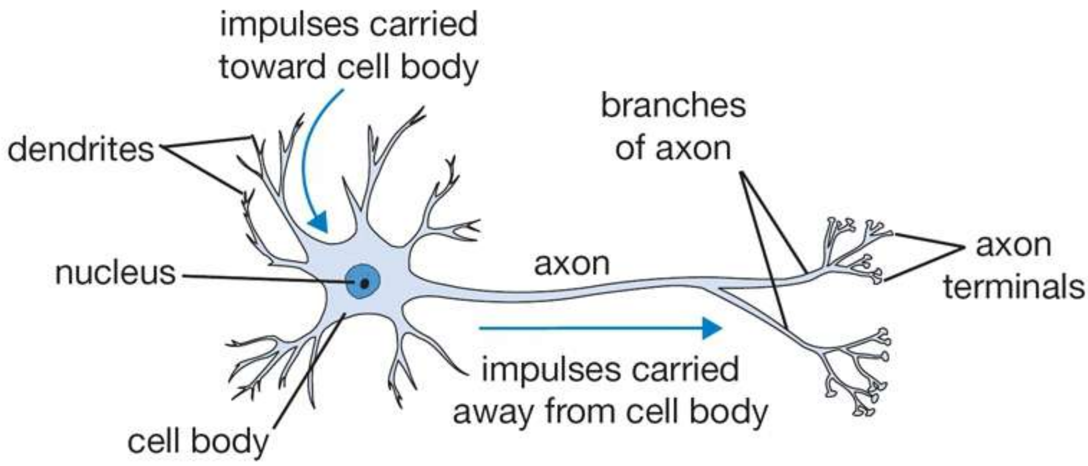

figure 10

6.2 WORKING OF BIOLOGICAL NEURON:

- **Dendrites** − Nerve cells (neurons) have extensive processes called dendrites. Tree-like branches, receiving the information from other neurons and contain specialized proteins that receive, process, and transfer these to the cell body. In other sense, we can say that they are like the ears of neuron.
- **Soma** − It is the cell body of the neuron contains the nucleus and other structures common to living cells and is responsible for processing of information, they have received from dendrites.
- **Axon** − It is just like a cable through which neurons send the information.
- **Synapses** − It is the connection between the axon and other neuron dendrites.

6.3 MODEL OF ARTIFICIAL NEURAL NETWORK:

Model of Artificial Neural Network (ANN) is shown in Figure 11. X_1, X_2, X_3, ….Xn are input and W_1, W_2, W_3……W_n are associated weights. Summation (∑) only calculate the weighted sum and forward the weighted some to activation function. Activation function generate a particular output on a given node based on input provided

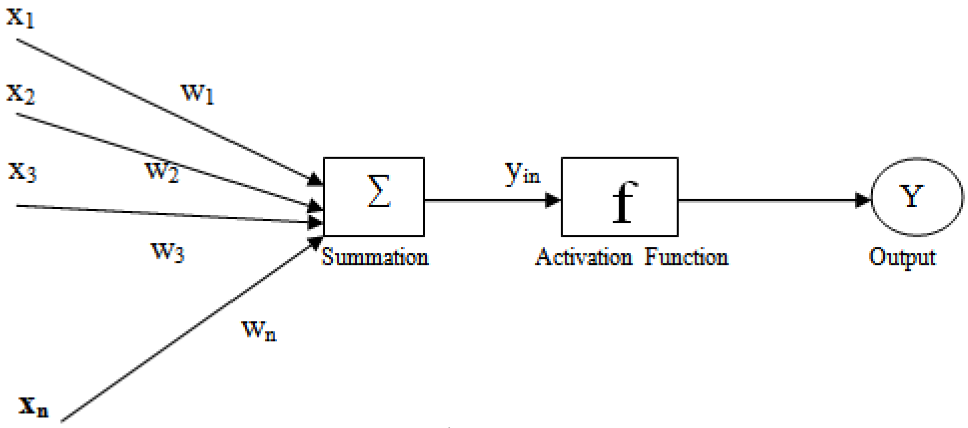

Figure 11

$Y_{in} = x_1w_1 + x_2w_2 + x_3w_3 + \ldots\ldots x_nw_n$

$$Y_{in} = \sum_{i}^{n} X_i . W_i$$

The output can be calculated by applying the activation function over the net input. There are three important type of activation function i.e Liner function, Heviside step function & Sigmoid function. Based on the requirement different activation functions are used.

VII. ARTIFICIAL NEURAL NETWORK ADAPTIVE CONTROLLER:

To achieve better time response Artificial Neural Network (ANN) is applied with adaptive controller. Proposed method improves the rise time, settling time, overshoot and steady state error. Artificial Neural Network having capability to handle highly time varying non liner system. Adaptation law based on the error signal of plant and reference model, accordingly tuning the weight of ANN to obtain optimum output. Artificial Neural Network (ANN) is applied with MRAC in presence of first order and second bounded and unmodeled dynamics to minimize the error. Proposed adaptive MRAC is shown in figure 12.

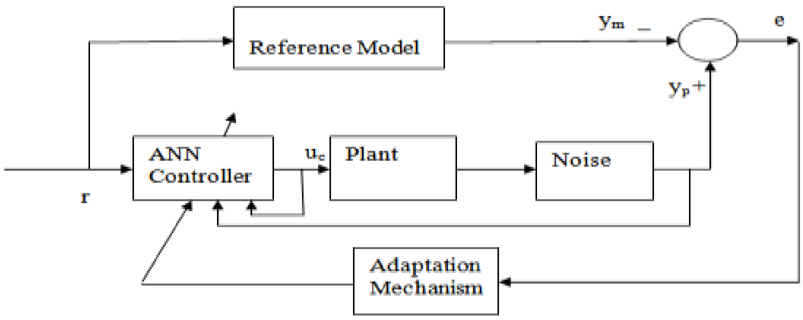

Figure 12

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VIII. ARTIFICIAL NEURAL NETWORK WITH MIT RULE IN PRESENT OF BOUNDED DISTRUBANCE AND UNMODELED DYNAMICS:

Consider the first order disturbance:

$$G_d = \frac{1}{s+1}$$

Time response for different value of adaption gain for MIT rule with Artificial Neural Network (ANN), in presence of first order disturbance is given below:

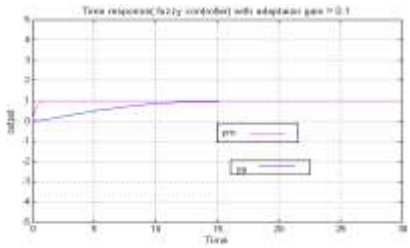

Figure 13

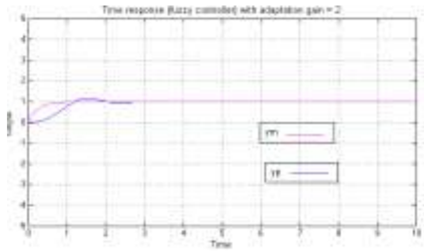

Figure 14

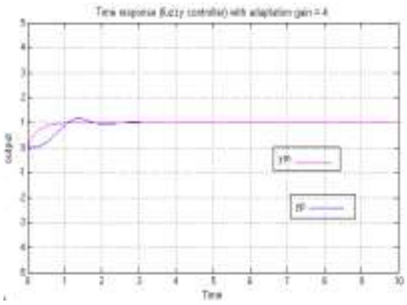

Figure 15

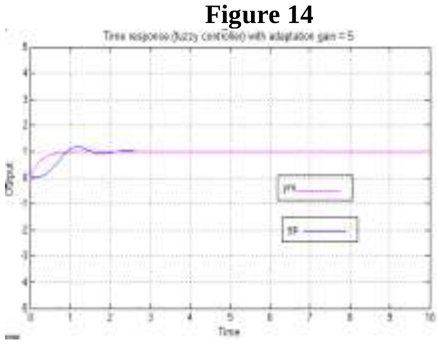

Figure 16

Simulation results with different value of adaptation gain for MIT rule in presence of first order bounded and unmodeled dynamics is summarized below:

	With Artificial Neural Network (ANN)			
	γ =0.1	γ =2	γ =4	γ =5
Maximum Overshoot (%)	0	10%	15%	19%
Undershoot (%)	0	1%	3%	5%
Settling Time (second)	11	5	4	2

With Artificial Neural Network (ANN), it is observed that overshoot, undershoot and settling time considerably has been improved even in presence of first order bounded and unmodeled dynamics, showing stability of the system.

Consider the second order disturbance:

$$G_d = \frac{25}{s^2 + 30s + 25}$$

Time response for different value of adaption gain for MIT rule with Artificial Neural Network (ANN), in presence of second order disturbance is given below:

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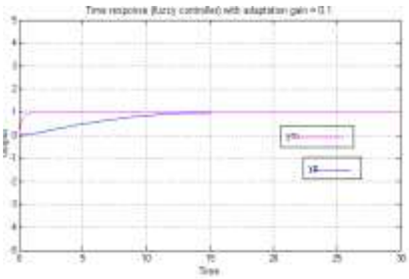

Figure 17

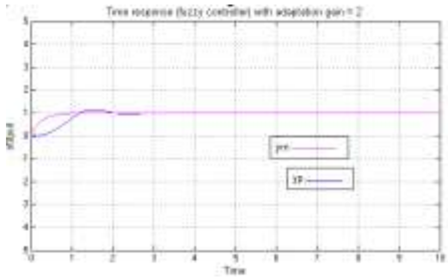

Figure 18

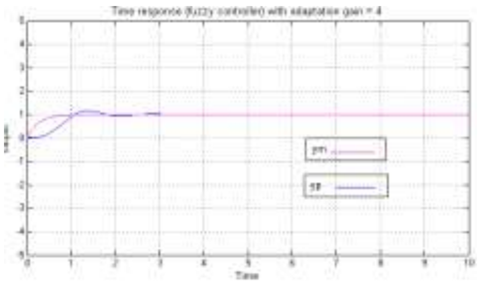

Figure 19

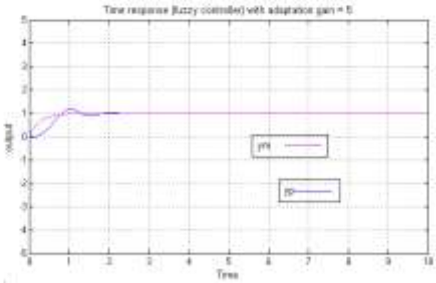

Figure 20

Simulation results with different value of adaptation gain for MIT rule in presence of second order bounded and unmodeled dynamics is summarized below:

	With Artificial Neural Network (ANN)			
	γ =0.1	γ =2	γ =4	γ =5
Maximum Overshoot (%)	0	12%	16%	19%
Undershoot (%)	0	2%	3%	5%
Settling Time (second)	15	5	4	3

With Artificial Neural Network (ANN),, it is observed that overshoot, undershoot and settling time considerably has been improved even in presence of second order bounded and unmodeled dynamics, showing stability of the system.

IX. CONCLUSION:

The use of Artificial Neural Network (ANN), gives that better result as compared to conventional Model Reference adaptive Controller. Comparison of result between conventional MRAC and with Artificial Neural Network (ANN), shows considerable improvement in overshoot, undershoot and settling time.

Time response is studied in the presence of first order & second order bounded and unmodeled dynamics using MIT rule with varying the adaptation gain using Artificial Neural Network (ANN). It is observed that, disturbance added in the conventional MRAC has some oscillations at the peak of signal is considered as a random noise. This noise has been reduced considerably by the use of Artificial Neural Network (ANN),. It can be concluded that Artificial Neural Network (ANN), shows better response and can be considered good enough for second order system in presence of first order & second order bounded and unmodeled dynamics. System performance may further improved by applying neuro-fuzzy in Model Reference Adaptive Control system in the presence of first order & second order bounded and unmodeled dynamics using MIT rule with varying the adaptation gain.

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