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A NOVEL MODEL REFERENCE INTELLIGENT ADAPTIVE CONTROL USING NEURAL NETWORK AND FUZZY LOGIC CONTROLLER

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ABSTRACT

In this paper two novel intelligent model reference adaptive controllers are proposed. In these schemes the intelligent supervisory loop is incorporated into the conventional model reference adaptive controller framework by utilizing an online growing neural / fuzzy network structure in parallel with it. In the conventional MRAC scheme, the controller is designed to realize plant output converges to reference model output based on the plant which is linear with disturbance free system. This scheme is for controlling linear plant effectively with unknown parameters. However, using MRAC to control the linear system with disturbance and nonlinearities at real time is difficult. In this paper, it is proposed to incorporate a neural / fuzzy controller in MRAC to overcome the problem. The control input is given by the sum of the output of conventional MRAC and the output of neural / fuzzy controller. The effectiveness of the proposed control schemes is demonstrated by simulations. The proposed schemes can significantly improve the system's behavior and force the system to follow the reference model and minimize the error between the model and plant output

Keywords: *Model Reference Adaptive Controller (MRAC), Neural Network (NN), Fuzzy Logic Controller(FLC)*

1. INTRODUCTION

Adaptive control provides adaptation mechanisms (adaptive laws) that adjust a controller for a controlled system (plant) with parametric, structural, or environmental uncertainties, to achieve desired system performance. Model reference adaptive control (MRAC) is a main approach of adaptive control. In MRAC, a reference model is chosen to generate the desired output trajectory, and the main task of MRAC is to ensure the output of the controlled system to track the output of the reference model system, in addition to closed-loop stability [1], [2].

Most adaptive control schemes have shown good convergence and stability in the ideal case; when no disturbances or noise act on the system and when its parameters are constant. However, in the presence of bounded disturbances, noise and time-varying parameters, not even the stability of adaptive control schemes can be guaranteed without introducing new control methodology,as in [3]. Therefore, robust adaptive control has become an important control strategy required for practical systems.In the 1980s, researchers have found that applying standard adaptive laws in the case of external acting disturbances is no longer possible, as the adaptive control objective of having a bounded error between the plant and reference outputs cannot be achieved. In addition, it was observed that other perturbations, such as time-varying parameters and un-modeled dynamics, could also result in unbounded signals in the system. Consequently, the need for robust adaptive controllers emerged, as in [4]-[7].

Narendra and parthasarathy [8] has shown in general indirect approach to nonlinear discrete time neuro – control scheme which consists of identification and adaptive control by using the [9],[10] that the NN – based adaptive control algorithm can cooperate well with identification of the nonlinear functions to realize a nonlinear adaptive control when the nonlinear adaptive

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control when the non linear control scheme is feedback linearizable. In [11] presented a fighter aircraft pitch controller evolved from a dynamic growing RBFNN in parallel with a model reference adaptive controller. The abilities of a neural network for nonlinear approximation and development for nonlinear approximation and the development of a nonlinear adaptive controller based on neural networks has been discussed in many works [12], [13]. A Neural Network Internal Model Control (NN- IMC) strategy is investigated in [14] by establishing inverse and forward model based neural network (NN).The use of neural networks for identification and control of non linear system has been demonstrated in [15] discusses a direct adaptive neural network controller for a class of non linear system. An Adaptive Inverse Model Control System (AIMCS) is designed for the plant, and two Radial Basis Function (RBF) neural networks are utilized in the AIMCS discussed in [16]. An adaptive-neuro-fuzzy-based sensor less control of a smart-material actuator is presented in [17]

It is well known that fuzzy technique has been widely used in many physical and engineering systems, especially for systems with incomplete plant information [18]-[23]. In addition to fuzzy logic, it has been widely applied to controller designs for nonlinear systems [24]-[28]. A novel fuzzy model reference based controller for controlling nonlinear plants can be found in [29]. Hugang Han [30] proposed an adaptive fuzzy controller for a class of nonlinear system with disturbance. A problem of Fuzzy-Approximation-Based adaptive control for a class of nonlinear time-delay systems with unknown nonlinearities and strict-feedback structure is discussed in [31]. Cheng-Wu Chen et al [32] discussed a proposed a method of stability analysis for a GA-Based reference ANNC which is capable of handling problems in a nonlinear system.

FL technique has been proposed to replace PI controllers in different error minimization applications [33], [34]. Various applications of FL have shown a fast growth in the past few years. FLC has become popular in the field of industrial control applications for solving control, estimation, and optimization problems [35]. An adaptive control approach for time-varying permanent-magnet synchronous motor (PMSM) systems with chaotic behavior is discussed in [36]. Observer-based model reference output feedback tracking control design for switched linear systems with time delay is investigated in [37]. A learning approach of combining MRAC with the use of fuzzy systems as reference models and controllers for control dynamical systems can be found in [38]. A hybrid approach by combining fuzzy controller and neural networks for learning-based control is proposed in [39].

The adaptive controller is used in various practical applications have attracted much attention in the field of control engineering. This is due to their promising potential for the tasks of tackling the presence of unknown parameters or unknown variation in plant parameters with better performance than those of constant gain feedback control law. In general, the external load disturbances always exist, although it is bounded. So, the controller without considering the disturbances can not stabilize the closed-loop control system. A solution to this problem is to incorporate dead-zone technique in the adaptive controller. With this approach, the controller will stop updating the control parameters when the identifier error is smaller than some threshold. Thus, it can prevent the estimated parameters from being infinity. However, the regulation error of the system will only be asymptotically bounded if large threshold is used, resulting in undesirable closed-loop performance. All control techniques have their individual characteristics. Hence, combining the merits of the adaptive control with that of the neural network control theories and then designing a new stabilizing controller will have better performance than that based on one control theory

In this paper, this point is addressed by presenting a novel intelligent model reference adaptive control schemes is proposed to replace the neural network controller used in conventional model reference adaptive scheme by a fuzzy logic controller. A FLC- MRAC scheme is proposed to improve the tracking performance. The fuzzy logic controller is used to compensate the disturbance and nonlinearity of the plant that is not taken into consideration in the conventional MRAC. The role of model reference adaptive controller is to perform the model matching for the uncertain linearized system to a given reference model.

The paper is organized as follows. Section 2 proposes the structure of an MRAC design. Section 3 describes the neural network -based model reference adaptive controller and 4 describe fuzzy logic controller-based model reference adaptive controller schemes. Section 5 analyses the result and discussion of the proposed schemes and the conclusions are given in section 6.

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2. STRUCTURE OF AN MRAC DESIGN

The MRAC is one of the major approaches in adaptive control. The desired performance is expressed as a reference model, which gives the wished response to an input signal. The adjustment mechanism changes the parameters of the regulator by minimizing the error between the system output and the reference model.

2.1 The Plant Model and Reference Model System

Sections To consider a Single Input and Single Output (SISO), Linear Time Invariant (LTI) plant with strictly proper transfer function

$$G(s) = \frac{y_p(s)}{u_p(s)} = K_p \frac{Z_p(s)}{R_p(s)} \quad (1)$$

where u_p is the plant input and y_p is the plant output .Also, the reference model is given by

$$G_m(s) = \frac{y_m(s)}{r(s)} = K_m \frac{Z_m(s)}{R_m(s)} \quad (2)$$

where r and y_m are the model's input and output. Define the output error as

$$e = y_p - y_m \quad (3)$$

Now the objective is to design the control input U_{mr} such that the output error, e goes to zero asymptotically for arbitrary initial condition, where the reference signal $r(t)$ is piecewise continuous and uniformly bounded. The plant and reference model satisfy the following assumptions.

Assumptions:

1. $Z_p(s)$ is a monic Hurwitz polynomial of degree m_p
2. An upper bound n of degree n_p of $R_p(S)$
3. The relative degree $n^* = n_p - m_p$ of $G(s)$
4. The sign of the high frequency gain K_p are known
5. $Z_m(s)$,$R_m(s)$ are monic Hurwitz polynomials of degree q_m, p_m respectively, where $p_m \le n$
6. The relative degree $n_m^* = p_m - q_m$ of $G_m(s)$ is the same as that of $G(S)$, i.e., $n_m^* = n^*$

2.2 Relative Degree n =1

As in Ref [1] the following input and output filters are used,

$$\dot{\omega}_1 = F\omega_1 + gu_p \quad (4)$$

$$\dot{\omega}_2 = F\omega_2 + gy_p$$

where F is an $(n-1)*(n-1)$ stable matrix such that $\det(SI - F)$ is a Hurwitz polynomial whose roots include the zeros of the reference model and that (F,g) is a controllable pair. It is defined as the "regressor" vector

$$\omega = [\omega_1^T, \omega_2^T, y_p, r]^T \quad (5)$$

In the standard adaptive control scheme, the control U_{mr} is structured as

$$U_{mr} = \theta^T \omega \quad (6)$$

where $\theta = [\theta_1, \theta_2, \theta_3, C_0]^T$ is a vector of adjustable parameters, and is considered as an estimate of a vector of unknown system parameters θ^*.

The dynamic of tracking error

$$e = G_m(s) p^* \tilde{\theta}^T \omega \quad (7)$$

Where $P^* = \frac{K_p}{K_m}$ and $\tilde{\theta} = \theta(t) - \theta^*$ represents parameter error. Now in this case, since the transfer function between the parameter error $\tilde{\theta}$ and the tracking error e is strictly positive real (SPR) [1], the adaptation rule for the controller gain θ is given by

$$\dot{\theta} = -\Gamma e_1 \omega \operatorname{sgn}(p^*) \quad (8)$$

where Γ is a positive gain.

2.3 Relative Degree n =1

In the standard adaptive control scheme, the control U_{mr} is structured as

$$U_{mr} = \theta^T \omega + \dot{\theta}^T \Phi = \theta^T \omega - \theta^T \Gamma \phi e_1 \operatorname{sgn}(K_p / K_m) \quad (9)$$

where $\theta = [\theta_1, \theta_2, \theta_3, C_0]^T$ is a vector of adjustable parameters, and is considered as an estimate of a vector of unknown system parameters θ^*.

The dynamic of tracking error is

$$e = G_m(s)(s + p_0) p^* \tilde{\theta}^T \phi \quad (10)$$

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where $P^* = \dfrac{K_p}{K_m}$ and $\tilde{\theta} = \theta(t) - \theta^*$ represent the parameter error. $G_m(s)(s+p_0)$ is strictly proper and Strictly Positive Real(SPR). Now in this case, since the transfer function between the parameter error $\tilde{\theta}$ and the tracking error e is SPR, [1] and the adaptation rule for the controller gain θ is given

$$\dot{\theta} = \Gamma \phi e_1 \operatorname{sgn}(K_p / K_m) \qquad (11)$$

where $e_1 = y_p - y_m$ and Γ is a positive gain.

The adaptive laws and control schemes developed are based on a plant model that is free from disturbances, noise and unmodelled dynamics. These schemes are to be implemented on actual plants that most likely to deviate from the plant models on which their design is based. An actual plant may be infinite in dimensions, nonlinear and its measured input and output may be corrupted by noise and external disturbances. It is shown by using conventional MRAC that adaptive scheme is designed for a disturbance free plant model and may go unstable in the presence of small disturbances.

3. NEURAL NETWORK-BASED MODEL REFERENCE ADAPTIVE CONTROL

To make the system adapt more quickly and more efficiently than conventional MRAC system, a new idea is proposed and implemented. The new idea which is proposed in this paper is the neural network based model reference adaptive control scheme (NN-MRAC). In this scheme, the controller is designed by using parallel combination of conventional MRAC system and neural network controller. The block diagram of the proposed MRAC with neural network is shown in fig.1. The theoretical basis for the proposed scheme is as follows,

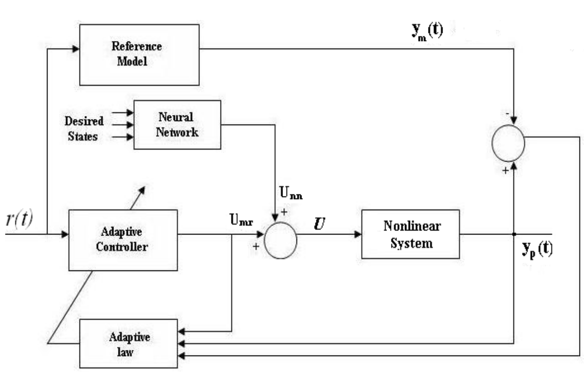

Figure 1. Block diagram of the NN-MRAC

Let the state model of linear time invariant system is given by the following form

$$X(t) = AX(t) + BU(t)$$
$$Y(t) = CX(t) + DU(t) \qquad (12)$$

This scheme is restricted to a case of single input single output control, noting that the extension to multiple input multiple output is possible. To keep the plant output y_p converges to the reference model output y_m, we synthesize the control input U by the following equation,

$$U = U_{mr} + U_{nn} \qquad (13)$$

where U_{mr} is the output of the adaptive controller, U_{nn} is the output of neural network and v is the disturbance signal

$$U_{mr} = \theta^T \omega$$
$$\theta = [\theta_1, \theta_2, \theta_3, C_0]^T \qquad (14)$$
$$\omega = [\omega_1, \omega_2, y_p, r]^T$$

Stability of the system and adaptability are then achieved by an adaptive control law U_{mr} tracking the system output to a suitable reference model, such that error $e = y_p - y_m = 0$ asymptotically. The controller design concept is illustrated using the following state equation of the second order system, which can be expanded to higher order system comfortably.

$$\dot{x}_1 = x_2 \qquad (15)$$
$$\dot{x}_2 = ax_1 + bx_2 + cU$$

where v is an external disturbance acts on the system and let the output,

$$y_p = x_1 \qquad (16)$$

Differentiating

$$\ddot{y}_p = \ddot{x}_1 = \dot{x}_2 = ax_1 + bx_2 + cU$$
$$U = c^{-1}(\dot{x}_2 - ax_1 - bx_2) \qquad (17)$$

Suppose a controller U_d can be established which should track a desired signal say $\dot{x}_{2d}$ then the controller equation can be written as

$$U_d = c^{-1}(\dot{x}_{2d} - ax_1 - bx_{2d}) \qquad (18)$$

which is the same as,

$$U_d = D(y_p, x_{2d}, \dot{x}_{2d}) \qquad (19)$$

where D is functional relation between states, control and output. Thus it possible to have a system response equals to desired value if the controller U_d can effectively inverse the system dynamics. In other words the controller U should

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track the system such that $\ddot{e} = 0$, However due to system dynamics, the error equation has to be written as,

$$e = (x_d - x) = 0$$

Thus the controller U should be written as

$$U = c^{-1}(\dot{x}_{2d} - ax_1 - bx_{2d}) + U_{mr} \qquad (20)$$

The neural network control law now becomes

$$U_d = D\ (y_p, x_{2d}, \dot{x}_{2d}) \qquad (21)$$

where y_p is the plant output .from the above discussion it can be seen that the input to the neural network should be

$$X = [y_p, x_{2d}, \dot{x}_{2d}] \qquad (22)$$

The design procedure multilayer back propagation neural network controller and derivation are discussed next

3.1 Structured of Proposed Multilayer Back propagation Neural Network Controller Design

The inputs of the neural network are the desired system states, its derivatives, and the plant. We used multilayer back propagation networks for the proposed method.

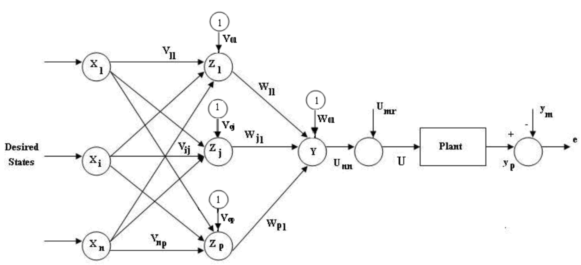

Figure 2.Structure of Neural Network

The multilayer back propagation network is especially useful for this purpose, because of its inherent nonlinear mapping capabilities, which can deal effectively for real-time online computer control. The NN of the proposed method has three layers: an input layer with *n* neurons, a hidden layer with *n* neurons and an output layer with one neuron as shown Fig 2. Let x_i be the input to the i^{th} node in the input layer, z_j be the input to the j^{th} node in the hidden layer, y be the input to the node in the output layers. Furthermore V_{ij} be the weight between the input layer and hidden layer W_{j1} is the weight between the hidden layer and the output layer.

3.2 Learning of NN

The relations between inputs and output of NN is expressed as,

$$Z_{-inj} = V_{oj} + \sum_{i=1}^{n} x_i V_{ij} \qquad (23)$$

$$Y_{-ink} = W_{01} + \sum_{j=1}^{P} z_j W_{j1} \qquad (24)$$

$$Z_j = F(Z_{-inj}) \qquad (25)$$

$$Y_k = F(Y_{-ink}) \qquad (26)$$

where F (.) is the activation function.
we chose sigmoid function for the activation function as follow

$$F(x) = \frac{2a}{1 + \exp(-\mu x)} - a \qquad (27)$$

where $\mu > 0$, a is a specified constant such that $a \leq 0$, and F(x) satisfies –a<F(x) <a
The aim of training to minimize the sum of square error energy function,

$$E(k) = \frac{1}{2}[y_m - y_p]^2 \qquad (28)$$

The weight are updated by using

$$\Delta W_{j1} = -\eta \frac{\partial E}{\partial W_{j1}} \qquad (29)$$

$$\Delta W_{01} = -\eta \frac{\partial E}{\partial W_{01}} \qquad (30)$$

$$\Delta V_{ij} = -\eta \frac{\partial E}{\partial V_{ij}} \qquad (31)$$

$$\Delta V_{0j} = -\eta \frac{\partial E}{\partial V_{0j}} \qquad (32)$$

where η is the learning role, $\frac{\partial E}{\partial W_{j1}}, \frac{\partial E}{\partial W_{01}}, \frac{\partial E}{\partial V_{ij}}$ and $\frac{\partial E}{\partial V_{oj}}$ are derived as follow,

$$\frac{\partial E}{\partial W_{j1}} = \frac{\partial E}{\partial y_p}\frac{\partial y_p}{\partial u_p}\frac{\partial u_p}{F(y_{-ink})}\frac{\partial F(y_{-ink})}{\partial y_{-ink}}\frac{\partial y_{-ink}}{dW_{j1}} \qquad (33)$$

$$\frac{\partial E}{\partial W_{01}} = \frac{\partial E}{\partial y_p}\frac{\partial y_p}{\partial u_p}\frac{\partial u_p}{F(y_{-ink})}\frac{\partial F(y_{-ink})}{\partial y_{-ink}} \qquad (34)$$

$$\frac{\partial E}{\partial V_{ij}} = \frac{\partial E}{\partial y_p}\frac{\partial y_p}{\partial u_p}\frac{\partial u_p}{F(y_{-ink})}\frac{\partial f(y_{-ink})}{dy_{-ink}}\frac{dy_{-ink}}{\partial F(Z_{-inj})}\frac{\partial f(z_{-inj})}{z_{-inj}}\frac{\partial z_{-inj}}{\partial V_{ij}} \qquad (35)$$

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$$\frac{\partial E}{\partial V_{0j}}=\frac{\partial E}{\partial y_p}\frac{\partial y_p}{\partial u_p}\frac{\partial u_p}{F(y_{-ink})}\frac{\partial f(y_{-ink})}{dy_{-ink}}\frac{dy_{-ink}}{\partial F(Z_{-inj})}\frac{\partial f(z_{-inj})}{z_{-inj}} \quad (36)$$

where

$$\frac{\partial E}{\partial y_p}=-(y_m-y_p) \quad (37)$$

$$\frac{\partial u_p}{\partial f(y_{-ink})}=1 \quad (38)$$

$$\frac{\partial y_{-ink}}{\partial W_{ji}}=F(z_{-inj}) \quad (39)$$

$$\frac{\partial y_{-ink}}{\partial f(z_{-inj})}=W_{j1} \quad (40)$$

$$\frac{\partial z_{inj}}{\partial Vij}=X_i \quad (41)$$

$$\frac{\partial F(y_{-ink})}{\partial (y_{-ink})}=\frac{\mu}{2a}[(a-F(y_{-ink)})(a+F(y_{\_ink)})] \quad (42)$$

$$\frac{\partial F(z_{-inj})}{\partial (Z_{-inj})}=\frac{\mu}{2a}(a-F(z_{-inj}))(a+F(z_{-inj})) \quad (43)$$

$$\frac{\partial y}{\partial U}=\frac{\partial y}{\partial U_{mr}}\frac{\partial U_{mr}}{\partial U} \quad (44)$$

$$=\frac{\partial y}{\partial U_{mr}}/\frac{\partial U}{\partial U_{mr}}$$

$$U=U_{mr}+U_{nn} \quad (45)$$

$$\frac{\partial U}{\partial U_{mr}}=1+\frac{\partial U_{nn}}{\partial U_{mr}}$$

(46)

$$\frac{\partial U_{nn}}{\partial U_{mr}}=\frac{\partial F(y_{-ink})}{\partial y_{-ink}}\frac{\partial y_{-ink}}{\partial F(z_{-inj})}\frac{\partial F(z_{-inj})}{\partial z_{-inj}}\frac{\partial z_{-inj}}{\partial X_i} \quad (47)$$

$$\frac{\partial z_{in-j}}{\partial x_i}=V_{ij} \quad (48)$$

$$W_{j1}(new)=W_{j1}(old)+\Delta W_{j1} \quad (49)$$

$$W_{01}(new)=W_{01}(old)+\Delta W_{01} \quad (50)$$

$$V_{ij}(new)=V_{ij}(old)+\Delta V_{ij} \quad (51)$$

$$V_{0j}(new)=V_{0j}(old)+\Delta V_{0j} \quad (52)$$

4. FUZZY LOGIC CONTROLLER-BASED MODEL REFERENCE ADAPTIVE CONTROL

In this section FLC is proposed to replace the neural network controller of NN-MRAC scheme and it used for error minimization. For the NN-MRAC scheme, the NN controller is generating a quantity, in such a way so as to minimize a specified error. Therefore, FLC can replace the conventional NN controller to solve the optimization problem. A Fuzzy Logic Controller-based Model Reference Adaptive Control (FLC-MRAC) scheme is proposed to improve the system performance. The controller structure proposed in this paper for the FLC-MRAC is shown in Figure 3 which consists of a parallel MRAC, and a FLC. While the MRAC forces the plant output to follow closely the output of the model which represents the desired closed loop behavior, and the FLC used for various operating conditions, the objective of the fuzzy logic control is to determine the control signal for controlling nonlinear processes and disturbance. The error and the change in error are given input to the FLC. The rules and membership function of FLC are formed from the input and output waveforms of NN controller of designed NN-MRAC. The block diagram of FLC-MRAC scheme is shown in Fig. 3.

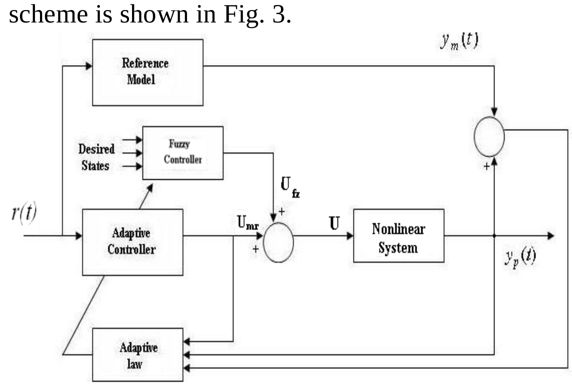

Figure. 3 Block diagram of the proposed FLC-MRAC

To keep the plant output y_p converges to the reference model output y_m, it is synthesize to control input U_{mf} by the following equation,

$$U=U_{mr}+U_{fz} \quad (53)$$

where U_{mr} is the output of the adaptive controller , U_{fz} is the output of the fuzzy logic controller and v is the disturbance signal

$$U_{mr}=\theta^T\omega$$

$$\theta=[\theta_1,\theta_2,\theta_3,C_0]^T \quad (54)$$

$$\omega=[\omega_1,\omega_2,y_p,r]^T$$

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where θ is the update law vector, and ω is the parameter vector.

The proposed FLC is a Mamdani-type rule base where the inputs are the error (e) and error change (ce) which can be defined as

$$e(k) = y_m(k) - y_p(k)$$

$$ce(k) = e(k) - e(k-1)$$

where $y_m(k)$ is the response of the reference model at k^{th} sampling interval, $y_p(k)$ is the response of the plant output at k^{th} sampling interval, $e(k)$ is the error signal at k^{th} sampling interval, $ce(k)$ is the error change signal at k^{th} sampling interval.

FLC consists of three stages: fuzzification, rule execution, and defuzzification. In the first stage, the crisp variables $e(kT)$ and $ce(kT)$ are converted into fuzzy variables error (e) and change in error (ce) using the triangular membership functions. Each fuzzy variable is a member of the subsets with a degree of membership varying between '0' (non-member) and '1' (full member).In the second stage of the FLC, the fuzzy variables error (e) and change in error (ce) are processed by an inference engine that executes a set of control rules containing in a rule base. In this paper the control rules are formulated using the input and output waveforms of the PI controller of designed PI-MRAC system behavior and the experience of control engineers. The reverse of fuzzification is called defuzzification. The FLC produces the required output in a linguistic variable (fuzzy number). According to real-world requirements, the linguistic variables have to be transformed to crisp output. As the centroid method is considered to be the best well-known defuzzification method, it is utilized in the proposed method. The feature of the proposed scheme is that the FLC can compensate for the nonlinearity of the system to linearize the dynamics from the output of the adaptive controller to the system output, while the role of the adaptive controller is to perform the model-matching for the linearized system.

4.1. Construction of Fuzzy Rules

In this paper the fuzzy rules are formulated by using the input and output waveforms of the neural controller of designed NN-MRAC and the experience of control engineers. Let us consider an example of a NN controller inputs: input 1, input 2 and NN controller output waveforms are given by Fig.4. Fuzzy rules and membership for error (e) and change in error (ce) and output (U_{fc}) are created by using the Fig. 4.The developed fuzzy rules are given in Table.1

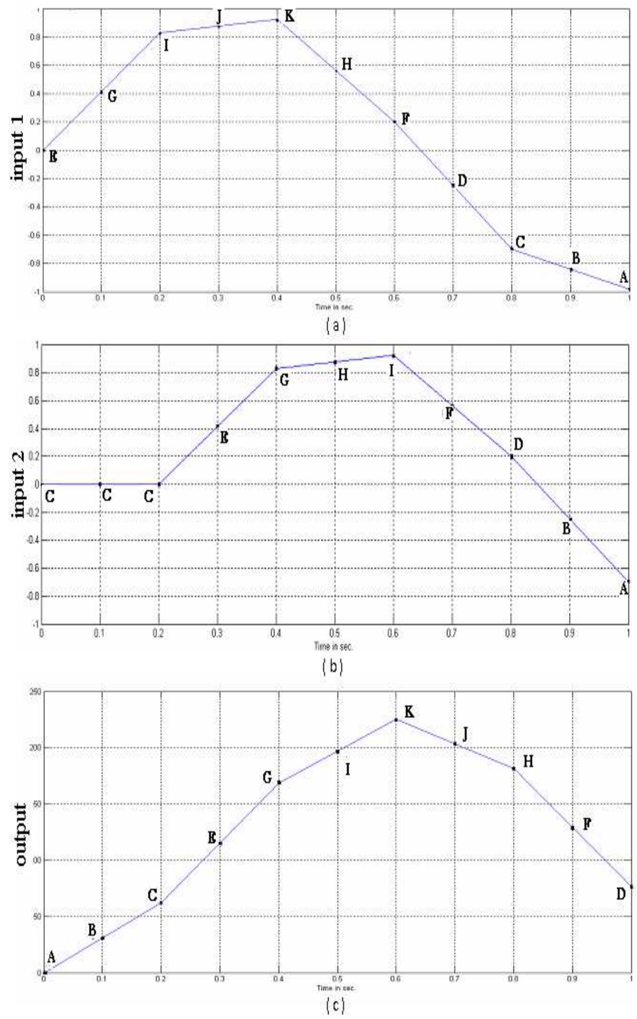

Figure. 4 NN controller inputs: (a) input 1, (b) input 2, (c) NN controller output

Table 1 Linguistic Rule Base

1.	If error is 'A' and change in error is 'A' then the output is 'D'
2.	If error is 'B' and change in error is 'B' then the output is 'F'
3.	If error is 'C' and change in error is 'D' then the output is 'H'
4.	If error is 'D' and change in error is 'F' then the output is 'J'
5.	If error is 'E' and change in error is 'C' then the output is 'A'
6.	If error is 'F' and change in error is 'I' then the output is 'K'

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7.	If error is ‘G’ and change in error is ‘C’ then the output is B
8.	If error is ‘H’ and change in error is ‘H’ then the output is ‘I’
9.	If error is ‘I’ and change in error is ‘C’ then the output is ‘C’
10.	If error is ‘J’ and change in error is ‘E’ then the output is ‘E’
11.	If error is ‘K’ and change in error is ‘G’ then the output is ‘G’

The membership functions for fuzzy variable input 1,input 2 and output are shown in Fig .5

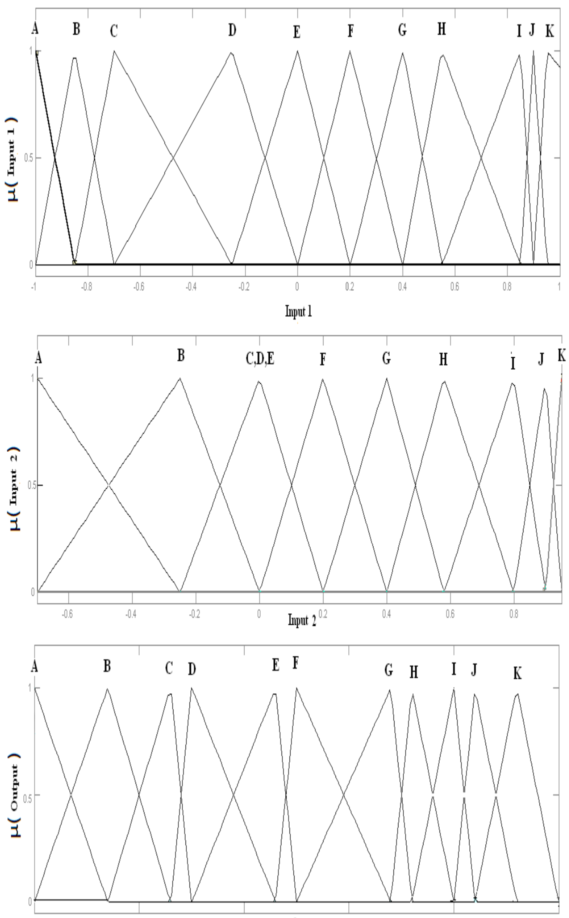

Fig. 5 Fuzzy Controller Input And Output Membership Functions. (A) Input 1. (B) Input 2. (C) Output

5. RESULTS AND DISCUSSION

In this section, the results of computer simulation for the conventional MRAC,NN-MRAC and FLC-MRAC scheme is evaluated by applying inputs of varying magnitude plus nonlinearities and disturbance in the plant. The same series of noise disturbance and nonlinearities has been applied for each simulation. The results show the effectiveness of the proposed schemes and reveal its performance superiority to the conventional MRAC technique. A detailed simulation comparison has been carried out using with an example. The simulation was carried out for the conventional MRAC, NN-MRAC and FLC-MRAC schemes with MATLAB for time duration t= [0, 30] s

5.1. System Data

The system set of data is as follows:
Transfer functions of the plant and reference models

$$G(S)=\frac{S+2.5}{S^3+6S^2+9S+1}$$

$$G_M(S)=\frac{S+2.5}{S^3+6S^2+11S+6}$$

which has relative degree n*= 2 The input to the reference model is chosen as r(t)= 2.4 The initial value of conventional MRAC scheme the controller parameters are chosen as θ(0) = [3, 18,-8, 3]^T. U_{mr} is the control input of the plant for conventionalMRAC

$$U_{mr}=\theta^T\omega+\dot{\theta}^T\Phi=\theta^T\omega-\theta^T\Gamma\phi e_1\,\mathrm{sgn}(K_p/K_m)$$

where $\theta=[\theta_1,\theta_2,\theta_3,C_0]^T$ is the update law vector, $\omega=[\omega_1,\omega_2,y_p,r]^T$ is the regressor vector and $\dot{\omega}_1=F\omega_1+gu_p$

$\dot{\omega}_2=F\omega_2+gy_p$ where F is an $(n-1)*(n-1)$ stable matrix such that det $(SI-F)$ is a Hurwitz polynomial whose roots include the zeros of the reference model and that (F,g) is a controllable pair.

In this example, the nonlinearity of backlash and disturbance are given by linear system is shown in Fig. 6

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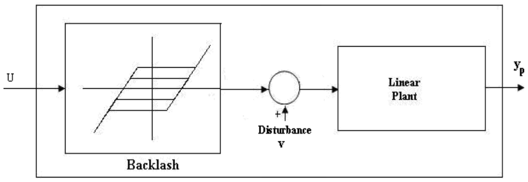

Fig. 6. Nonlinear System

In the neural network based model reference adaptive controller, the NN has three layers: an input layer with 4 neurons, a hidden layer with 4 neurons and an output layer with one neuron. The input to the neural network should be $X = [y_p, x_{2d}, \dot{x}_{2d}, \ddot{x}_{2d}]$

The U is the control input of the nonlinear for the NN-MRAC scheme.

$$U = U_{mr} + U_{nn}$$

The simulink model of the proposed NN-MRAC developed is given in fig .7

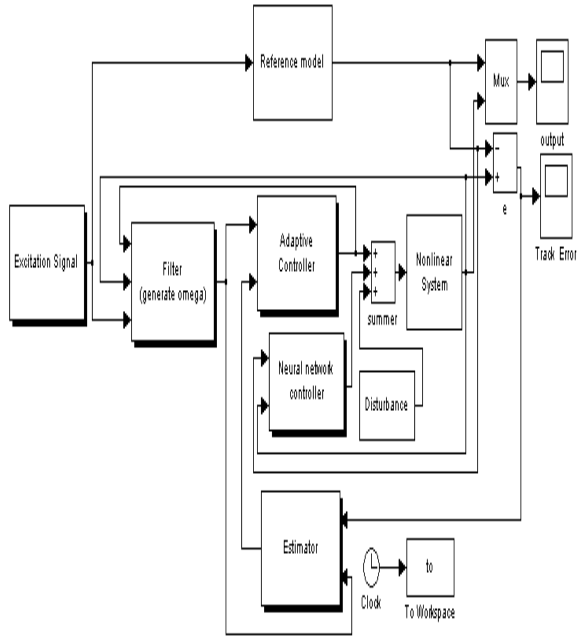

Figure. 7. Simulink Model of the NN- MRAC system

To obtain optimal performance compared to NN-MRAC scheme, FLC-MRAC is employed. The fuzzy system structure consists of four inputs and one output. These inputs can be represented as $X = [y_p, x_{2d}, \dot{x}_{2d}, \ddot{x}_{2d}]$.

In this paper, a multiple-input single-output fuzzy system has been used. In this case where the fuzzy rule base consists of rules in the following form:

RB$_j$: IF x_1 is A_1^j AND x_2 is A_2^j ……x_n is A_n^j THEN u is B^j

Where j 1,2,………,M

x_i i = (1,2,………,M) input variables to the fuzzy system;

u output variable of the fuzzy system;

A_1^j and B^j linguistic terms characterized by fuzzy membership functions and , respectively.

There are 60 rules that have been developed based on these input vector and membership functions. The details of the input and output membership functions are shown in Fig. 7.

The fuzzy rules and membership functions are formulated using the input and output waveforms of the NN of designed NN-MRAC scheme and the experience of control engineers. Each variable of the FLC has five membership functions. The following fuzzy sets are used: VVS (Very Very Small), VS (Very Small), S (Small), M (Medium) and L (Low)

The U_{mf} is the control input of the plant for the FLC-MRAC scheme.

$$U_{mf} = U_{mr} + U_{fz}$$

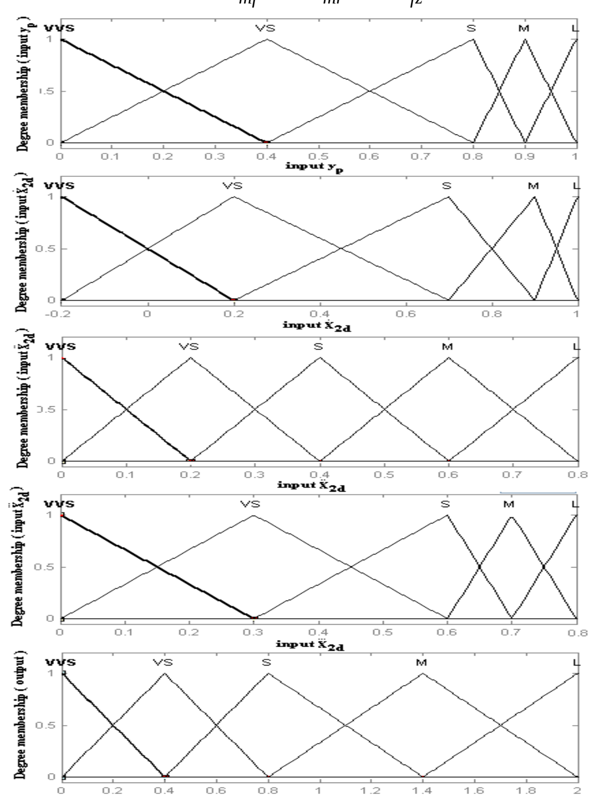

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Figure.8 Membership function for inputs and output

The simulink model of the FLC-MRAC scheme is given in Fig .9

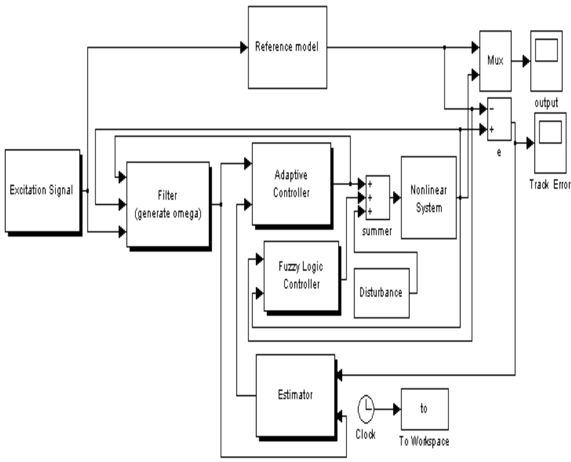


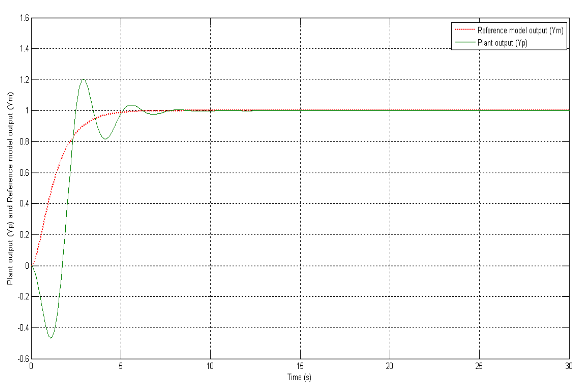
Figure. 9 Simulink Model of the FLC- MRAC system

5.2. Disturbance and nonlinearities-Free Case with input r(t) =2.4

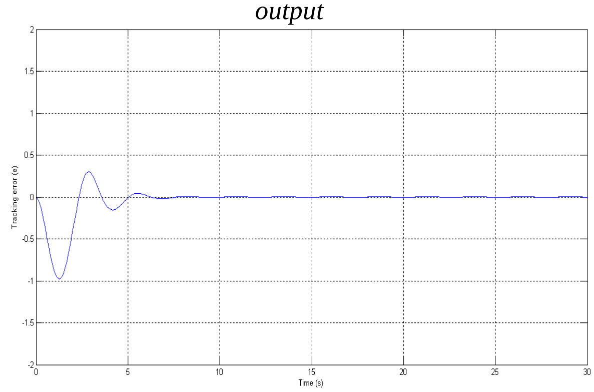
Fig. 10 show the performance of the MRAC with input r(t)= **2.4**.In this case there is no disturbance and nonlinearities are given in the plant

5.3. Disturbance and nonlinearities- Present Case with input r(t) =2.4

While an external disturbance $v_d = 2 \cos (0.7t)$ and nonlinearity component backlash with dead bandwidth M=10 are acts on the system. Figs. 11–13 show the performance of the MRAC, NN-MRAC and FLC-MRAC scheme for example 1 with input r(t)= 2.4 plus disturbance and nonlinearities in the plant

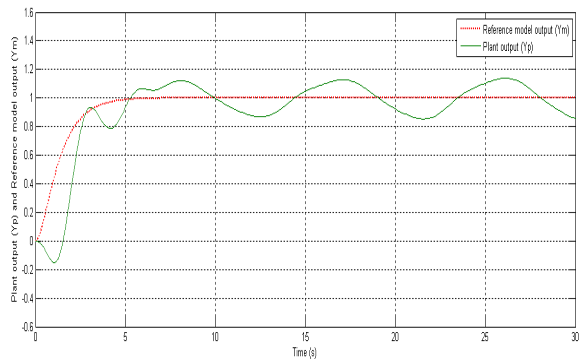


(a)



(b)

Figure.. 10 Response of the conventional MRAC scheme without disturbance :(a) Plant and model reference response; (b) Tracking error



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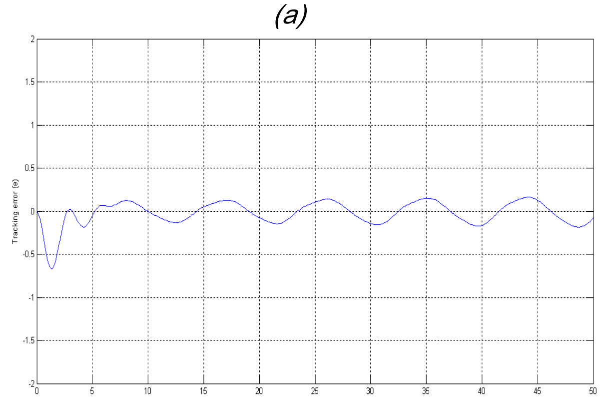

Figure.. 11 Response of the conventional MRAC scheme with disturbance and nonlinearities :(a) Plant and model reference response; (b) Tracking error

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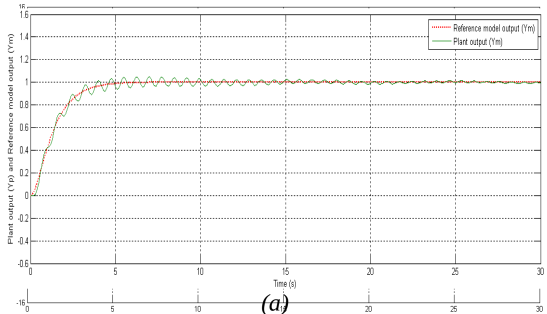
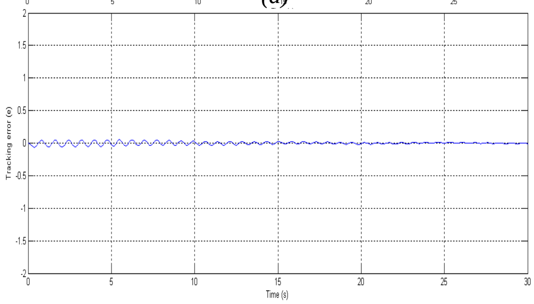
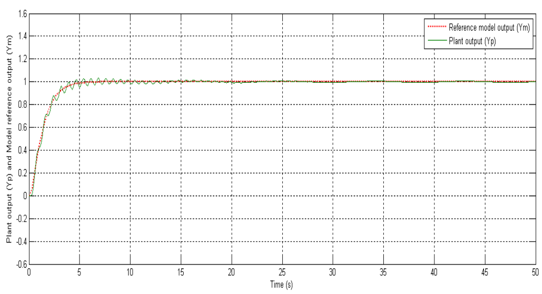


(a)

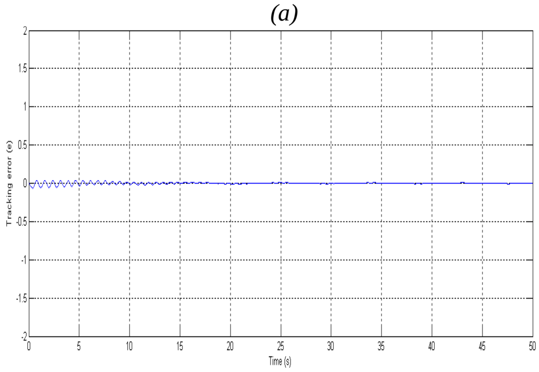


(b)

Figure. 12 Response Of The NN- MRAC Scheme With Disturbance And Nonlinearities :(A) Plant And Model Reference Response; (B) Tracking Error



(a)



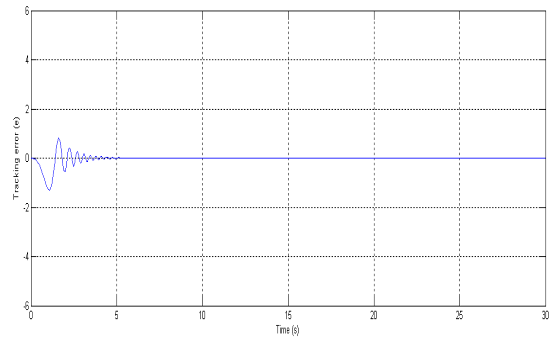
(b)

Figure. 13 Response Of The FLC- MRAC Scheme With Disturbance And Nonlinearities :(A) Plant And Model Reference Response; (B) Tracking Error.

5.4. Disturbance-Free Case with input r(t) = r(t)= 20sin0.5t

Fig. 14 show the performance of the MRAC with input r(t)= 20sin0.5t and no disturbance and nonlinearities are given in the plant

(a)

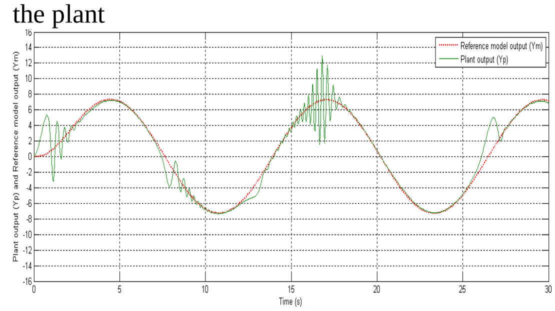


(b)

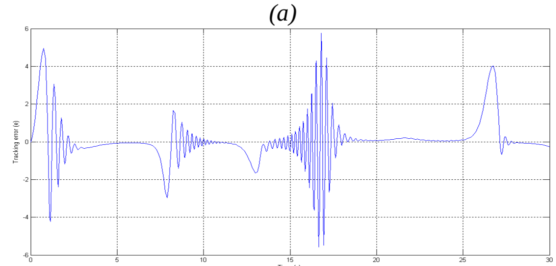
Figure. 14 Response Of The MRAC Scheme With No Disturbance And Nonlinearities :(A) Plant And Model Reference Response; (B) Tracking Error

5.5. Disturbance and nonlinearities -Present Case with input r(t)= 20sin0.5t

Figs. 15–17 show the performance of the MRAC, NN-MRAC and FLC-MRAC scheme with input r(t)= 20sin0.5t plus disturbance v(t)= 21sin0.7t+30cos0.9t and nonlinearity component backlash with dead bandwidth M=15 are given in the plant



(a)



(B)

Figure.. 15 Response Of The Conventional Mrac Scheme With Disturbance And Nonlinearities :(A) Plant And Model Reference Response; (B) Tracking Error

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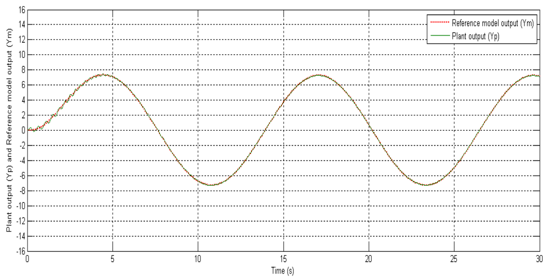
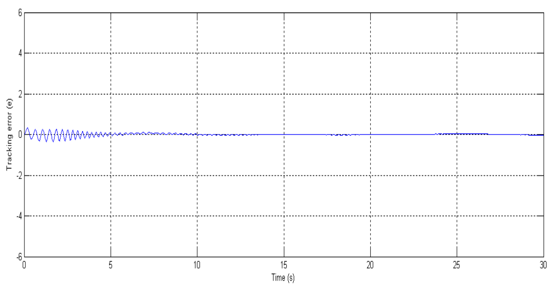
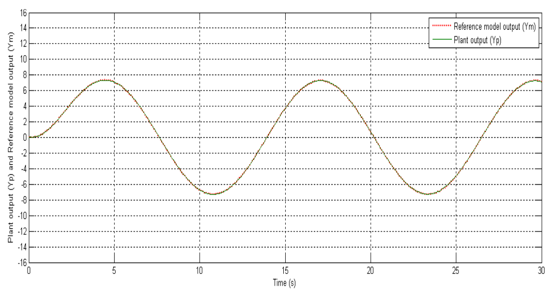


(a)

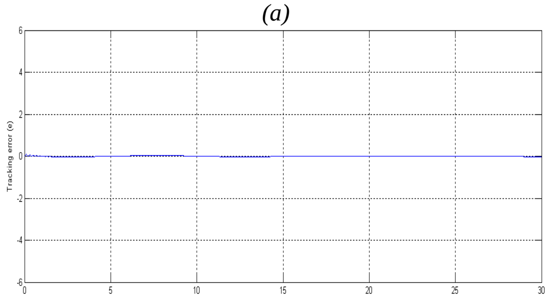


(b)

Figure. 16 Response Of The NN- MRAC Scheme With Disturbance And Nonlinearities: (A) Plant And Model Reference Response; (B) Tracking Error



(a)



(b)

Figure. 17 Response Of The NN- MRAC Scheme With Disturbance And Nonlinearities: (A) Plant And Model Reference Response; (B) Tracking Error

Figs. 10 and 14 show the response of the conventional MRAC scheme without disturbance and nonlinearities. It is shown that the plant output is tracks with the reference model output and the tracking error approaches the zero. The performance of the conventional MRAC, NN-MRAC and FLC-MRAC scheme is evaluated by applying inputs plus disturbance and nonlinearities in the plant. The results show the effectiveness of the proposed schemes to force the plant to follow the model, under uncertainties. Extensive simulation tests were carried out to compare the three adaptation schemes: conventional MRAC, NN- MRAC scheme and FLC-MRAC. In the simulation results of conventional MRAC, NN-MRAC and FLC-MRAC schemes, the dotted line and solid line represents the model reference trajectory and plant trajectory respectively. In conventional MRAC scheme, the plant output is poor with large overshoots and oscillations as shown in Figs. 11 and 15.

In the proposed NN-MRAC scheme, the overshoots and the oscillations are much smaller, yielding a much better performance than the conventional MRAC scheme as shown in Figs.12 and 16. However, the application of the NN-MRAC scheme does not considerably improve the steady-state performance. In the proposed FLC- MRAC scheme the plant output has tracked with the reference model output and the tracking error becomes zero within 4 seconds with less control effort as shown in Figs.13 and 17 and which gives the optimal performance than the other methods. The FLC- MRAC scheme improves the transient and steady state performance.

The responses performed by the MRAC scheme are observed to be inferior to that of the NN-MRAC and FLC-MRAC schemes. Also, the response of the MRAC shows large overshoot and oscillation. Further, the response of the output performed by the NN-MRAC and FLC-MRAC scheme shows more satisfactory results for the bounded disturbances with unknown as well as time-varying characteristics than that of the MRAC.

From the above simulations, it is shown that the control algorithm using only MRAC scheme can guarantee that the tracking error approaches the zero if there are no disturbances and uncertainties, and plant output converges to the reference model output. However, it is said that only using the MRAC scheme will not stabilize the controlled systems with disturbances.

From the simulation results, because of the existing bounded disturbances and nonlinearities, the controlled system using the control algorithm only using the model reference adaptive controller will be unstable. When using the neural network and the model reference adaptive controller in coordination in which the control law is provide better performance and improve the steady state performance. But when using the fuzzy logic

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controller and the model reference adaptive controller in coordination in which the control law is used to cope with bounded disturbances and nonlinearities, the controlled system can be robustly stabilized all the time. From the above discussions, the proposed control algorithm both with the fuzzy logic controller and the conventional model reference adaptive controller can be a promising way to tackle the problem of controlling the systems with bounded time-varying disturbances and nonlinearities.

From the above simulations, it is shown that the control algorithm using only the model reference adaptive controller will not stabilize the controlled systems with disturbances and nonlinearities. From Figs.12 and 16, it is seen that the control algorithm both with the neural network control and the model reference adaptive controller working in coordination to improve the steady state performance. From Figs.13 and 17, it is seen that the control algorithm both with the fuzzy logic control and the model reference adaptive controller working in coordination can cope up with the uncertain dynamic system and bounded disturbances, but the control algorithm without the neural network or fuzzy logic network compensating control cannot. The proposed NN-MRAC scheme shows better control results compared to those by the conventional MRAC .Moreover, the FLC- MRAC scheme shows faster and optimal response compared to the MRAC scheme and NN-MRAC scheme.

From these simulation results it is observe that:

1. In conventional MRAC the plant output is not tracked with the reference model output. The conventional MRAC fails completely under the action of the external disturbance and nonlinearities, where a degradation in the performance due to overshoot is observed.

2. The proposed NN- MRAC scheme shows better control results compared to those by the conventional MRAC. The NN-MRAC scheme is improve the transient performance. However, the NN-MRAC scheme does not considerably improve the steady-state performance.

4. The proposed FLC-MRAC design approach can keep the plant output in track with the reference model and tracking error becomes zero within 4 seconds. The proposed FLC-MRAC controller gives better performances in terms of steady-state error, settling time and overshoot. The FLC-MRAC scheme is improve the both steady-state performance and transient performance. Hence it can be concluded that the proposed FLC-MRAC scheme is more robust performance than the other schemes.

On the contrary, the proposed method has much less error than the conventional method in spite of nonlinearities and disturbance. The simulation results have confirmed the efficiency of the proposed FLC-MRAC scheme for applying disturbances and nonlinearities.

5.6. Implementation issue

The proposed method can be widely used in most of the industrial nonlinear and complex applications such as machine tools, industrial robot control, position control, and other engineering practices. The proposed FLC-MRAC is relatively simple and does not require complex mathematical operations. It can be readily implemented using conventional rnicroprocessors or microcontrollers. The execution speed of the FLC-MRAC scheme can be improved by using advanced processors such as reduced instruction set computing (RISC) processors or digital signal processors (DSP's) or ASIC's (application specific integrated circuits).

6. CONCLUSION.

In FLC-MRAC the fuzzy rules and membership functions are formed from the input and output waveforms of NN controller of NN- MRAC scheme. A detailed simulation comparison has been carried out using with example. The proposed FLC-MRAC controller shows very good tracking results when compared to the conventional MRAC and the NN-MRAC scheme. Simulations and analyses have shown that the steady state performance and transient performance can be substantially improved by proposed FLC-MRAC scheme In proposed FLC-MRAC scheme, the system output tracks very closely the reference model in spite of the disturbances and nonlinearities. Thus the FLC-MRAC controller is found to be extremely effective, efficient and useful. Due to its simple operation, the proposed FLC-MRAC can be readily implemented using conventional microprocessors.

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