DESIGN OF MODEL REFERENCE ADAPTIVE INTELLIGENT CONTROLLER   USING NEURAL NETWORK FOR NONLINEAR SYSTEMS

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Abstract: In this paper a new approach to a neural network-based model reference adaptive intelligent controller is proposed. In this scheme, the intelligent supervisory loop is incorporated into the conventional model reference adaptive controller framework by utilizing an online growing multilayer back propagation neural network structure in parallel with it. The idea is to control the plant by conventional model reference adaptive controller with a suitable single reference model, and at the same time respond to plant by online tuning of a multilayer back propagation neural controller. In the conventional model reference adaptive control (MRAC) scheme, the controller is designed to realize plant output converges to reference model output based on the plant which is linear. This scheme is for controlling linear plant effectively with unknown parameters. However, using MRAC to control the nonlinear system at real time is difficult. In this paper, it is proposed to incorporate a Neural Network (NN) in MRAC to overcome the problem. The control input is given by the sum of the output of conventional MRAC and the output of NN. The NN is used to compensate the   nonlinearity of the plant that is not taken into consideration in the conventional MRAC. The proposed NN-based model reference adaptive controller can significantly improve the system behavior and force the system to follow the reference model and minimize the error between the model and plant output. The effectiveness of the proposal control scheme is demonstrated by simulations.

Key words: Model Reference Adaptive Controller (MRAC), Artificial Neural Network (ANN), Backlash and Dead zone.

1. Introduction

In the adaptive literature, the question of control of nonlinear systems with present day sophistication and complexities has often been an important research area due to the difficulties in accurately modeling, estimating system nonlinearities and uncertainties. Model Reference Adaptive Control (MRAC) is one of the main schemes used in adaptive system. Recently MRAC has received considerable attention, and many new approaches have been applied to practical processes [1], [2]. In the model reference adaptive control scheme, the controller is designed to realize plant output converges to reference model output based on the assumption that the plant can be liberalized. Therefore this scheme is effective for controlling linear plants with unknown parameters. However, it may not assure for controlling nonlinear plants with unknown structure. In recent years, the Artificial Neural Network (ANN) has become very popular in many control applications due to their higher computation rate and ability to handle nonlinear system. Some of the relevant research work including ANN as a part of control scheme is illustrated below. A robust adaptive control of uncertain nonlinear system using neural network is discussed in [3].Various types of neural network (NN) have been efficiently utilized in identification of nonlinear systems [4], [5]. A variety of algorithms are utilized to adjust the weight of the NN. In a typical multilayered NN, the weights in the layers can be adjusted to minimize the output error between the NN output and the observed output. The back propagation algorithm for efficiently updating the weight is useful in many applications such identification of nonlinear systems. Off-line iterative algorithm can be employed in the care of identification or modeling. However, in the aspect of control, the NN should work in online manner. In the control system structure, the output of NN is the control input to the nonlinear controlled system. i.e., there is the unknown nonlinear system between the NN and the output error. In this case, in order to apply any learning rules, we need the derivatives of the system output with respect to the input [6]. Kawalo et al. [7] presented a simple structure of NN- based feed forward controller which is equivalently an inverse of the controlled system after the NN completes the learning of the weights which are adjusted to minimize the feedback error. Narendra et al. [8] discussed the neural networks and they can be used effectively for the identification and control of nonlinear dynamical systems. Chen [9] proposed a back propagation neural networks for non linear self – tuning adaptive

control and Liu et al. [10] presented an adaptive control of nonlinear continuous – time systems using neural network. Kamalasudan et al. [11] presented a fighter aircraft pitch controller evolved from a dynamic growing Radial Basis-Function Neural Network (RBFNN) in parallel with a model reference adaptive controller. The abilities of a neural network for nonlinear approximation and the development of a nonlinear adaptive controller based on neural networks have been discussed in many works [12]-[13]. In particular, the adaptive tracking control architecture proposed in [14] is evaluated as a class of continuous-time nonlinear dynamic systems for which an explicit linear parameterization of uncertainty is either unknown or impossible. The use of neural networks for identification and control of nonlinear system has been demonstrated in [15] and it discusses a direct adaptive neural network controller for a class of nonlinear system. An online Radial Basis-Function Neural Network (RBFNN) in parallel with a Model Reference Adaptive Controller (MRAC) is discussed in [16]. A neuro-sliding mode approach based on Model Reference Adaptive Control (MRAC) is proposed in [17]. An adaptive-neuro-fuzzy-based sensorless control of a smart-material actuator is presented in [18]. 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 [19]. Xiang-Jie Liu et al. [20] discussed an Adaptive Inverse Model Control System (AIMCS) and it is designed for the plant, and two Radial Basis Function (RBF) neural networks are utilized in the AIMCS. A Model Reference Adaptive Control (MRAC)-based current control scheme of a PM synchronous motor with an improved servo performance is presented in [21]. Fadali, et al. [22] presented a robust adaptive control approach using Model Reference Adaptive Control (MRAC) for autonomous robot systems with random friction. An adaptive output-feedback control scheme is developed for a class of nonlinear SISO dynamic systems with time delays [23].

In this paper a proposal neural network-based model reference adaptive controller is designed from a multilayer back propagation neural network in parallel with a model reference adaptive controller. The control input is given by the sum of the output of adaptive controller and the output of neural network. The neural network is used to compensate the 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 network weights are adjusted by multilayer back propagation algorithm which is carried out in online. Finally to confirm the effectiveness of proposed method, we compared the simulation results of the conventional MRAC with the proposed method. The paper is organized as follows. Section 2 proposes the problem statement and section 3 discusses the structure of an MRAC design. Section 4 describes the proposed approach. Section 5 analyses the result and discussion of the proposed scheme and the conclusions are given in section 6. In this paper a proposal MRAC is designed from a multilayer back propagation neural network in parallel with a model reference adaptive controller.

2. Statement of the Problem

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

$$G(s) = \frac{y_P(s)}{u_p(s)} = K_P \frac{Z_p(s)}{R_P(s)} \tag{1}$$

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

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

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

$$e = y_p - y_m \tag{3}$$

Now the objective is to design the control input u such as 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

3. Structure of an MRAC design

3.1. Relative Degree n =1

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

$$\dot{\omega}_1 = F\omega_1 + gu_p \tag{4}$$
$$\dot{\omega}_2 = F\omega_2 + gy_p$$

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. We define the "regressor" vector

$$\omega = [\omega_1^T, \omega_2^T, y_p, r]^T \tag{5}$$

In the standard adaptive control scheme, the control u is structured as

$$u = \theta^T \omega \tag{6}$$

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

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

where $P^* = \dfrac{k_p}{k_m}$ and $\tilde{\theta} = \theta(t) - \theta^*$

represents parameter error. Now in this case, 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

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

where Γ is a positive gain.

3.2. Relative Degree n =2

In the standard adaptive control scheme, the control u is

structured as

$$u = \theta^T \omega + \dot{\theta}^T \Phi = \theta^T \omega - \theta^T \Gamma \phi e_1 \, \text{sgn}(K_p / K_m) \qquad (9)$$

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

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

where $p^* = \dfrac{k_p}{k_m}$ and $\tilde{\theta} = \theta(t) - \theta^*$ represent the parameter error. The equation, $G_m(s)(s + p_0)$ 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 Strictly Positive Real (SPR), [1], the adaptation rule for the controller gain θ is given

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

where $e_{1=} y_p\text{-}y_m$ 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 are 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.

When the disturbances and nonlinear component are added to the input of the plant of the conventional model reference adaptive controller in such a way that the tracking error has not come to zero and the output of the plant output is not tracked with the reference model plant output. The large amplitude of oscillations will come to the entire period of the plant output and the tracking error has not come to zero .The disturbance is considered as a random noise signal. To improve the system performance, the neural network-based model reference adaptive controller proposed, the controller is designed by using parallel combination of conventional MRAC system and neural network controller. The control signal coming from the MRAC is added to the neural network controller and then given to the plant input.

4. Proposed Approach

To make the system more quickly and efficiently adaptable 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 controller. 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 neural network-based model reference adaptive controller is shown in Fig. 1. The theoretical basis for the proposed scheme is as follows,
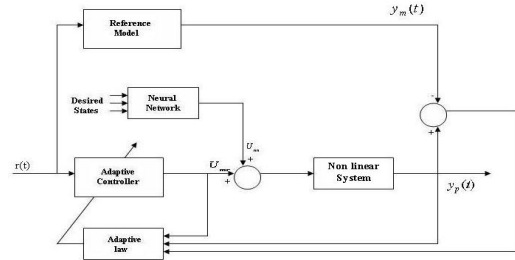

Fig. 1 Block diagram of the proposed MRAC

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

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

This scheme is restricted to a case of Single Input Single Output (SISO) control, noting that the extension to Multiple Input Multiple Output (MIMO) is possible. To keep the plant output y_p converges to the reference model output y_m, it is 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

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

Stability of the system and adaptability are then achieved by an adaptive control law *Umr*. By tracking the system state x to a suitable reference model, the error becomes 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.

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

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 $\dot{x}_{2d}$, and 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 is possible to have a system response equal to the desired value, if the controller U_d can effectively inverse the system dynamics. In other words the controller U should track the system in such a way 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

$$U_d = D^{-1}(y_p, x_{2d}, \dot{x}_{2d}) \qquad (21)$$

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

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

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

4.1. Structure 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. Here the multilayer back propagation neural network is used in the proposed method. 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 in Fig. 2.

Let x_i be the input to the ith node in the input layer, z_j be the input to the jth node in the hidden layer, y be the input to the node in the output layers. Furthermore V_{ij} is the weight between the input layer and hidden layer. W_{j1} is the weight between the hidden layer and the output layer.
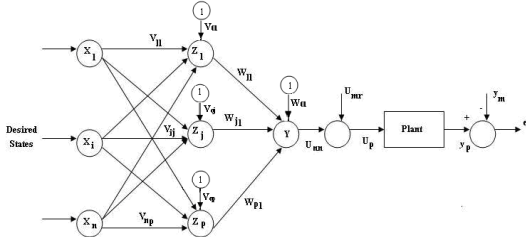

Fig. 2 Structure of Neural Network

4.2. 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.

The sigmoid function for the activation function chosen follows

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

where $\mu > 0$, a is a specified constant such as 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 is

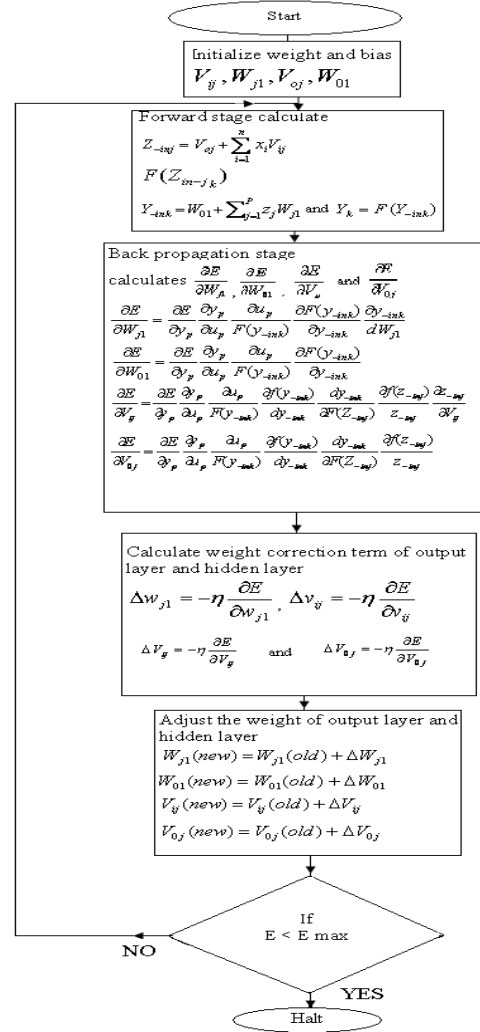$$E(k) = \frac{1}{2}[y_m - y_p]^2 \qquad (28)$$

Fig. 3 Proposed BPT Algorithm flow chart

The weights 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, $\dfrac{\partial E}{\partial W_{j1}}$, $\dfrac{\partial E}{\partial W_{01}}$, $\dfrac{\partial E}{\partial V_{ij}}$ and $\dfrac{\partial E}{\partial V_{0j}}$

are derived as follow,

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

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

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

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

where

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

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

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

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

$$\frac{\partial z_{inj}}{\partial V_{ij}} = X_i \tag{41}$$

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

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

$$\frac{\partial y}{\partial U} = \frac{\partial y}{\partial U_{mr}}\frac{\partial U_{mr}}{\partial U} \tag{44}$$

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

$$U = U_{mr} + U_{nn} \tag{45}$$

$$\frac{\partial U}{\partial U_{mr}} = 1 + \frac{\partial U_{nn}}{\partial U_{mr}} \tag{46}$$

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

$$\frac{\partial z_{in-j}}{\partial x_i} = V_{ij} \tag{48}$$

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

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

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

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

The structure of proposed multilayer back propagation neural network controller design is represented in the form of flowchart and it is shown in Fig. 3. In this proposed neural network based MRAC method, the tracking error became zero within 4 seconds and no oscillation has occurred. The plant output has tracked with the reference model output. This method is better than conventional MRAC system.

5. Results and Discussion

In this section, the result of the computer simulations for conventional MRAC and neural network-based MRAC system is reported. The result shows that the effectiveness of the proposed neural network-based MRAC scheme and its performance is superior to the conventional MRAC technique. The simulink model of the proposed intelligent MRAC developed is given in Fig. 4.
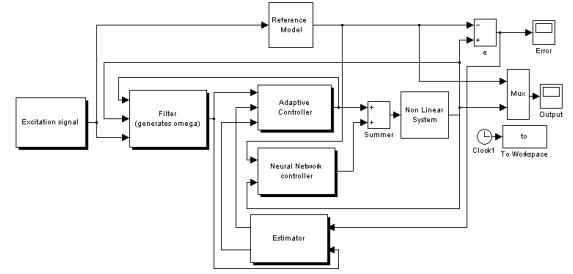

Fig. 4 Simulink Model of the proposed intelligent MRAC system

Example 1:

In this example, the nonlinearity of backlash is followed by linear system is shown in Fig. 5.
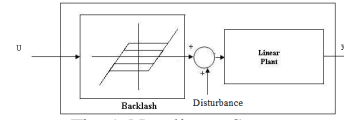

Fig.5. Non linear System

The disturbance (random noise signal) is also added to the input of the plant.

The linear part of the controlled system and the reference model are given below:

$$G(S) = \frac{S^2 + 4S + 3.75}{S^2 + 5S^2 + 7S + 2.25}$$

$$G_M(S) = \frac{S^2 + 4S + 3.75}{S^3 + 6S^2 + 11S + 6}$$

The initial value of the conventional MRAC scheme controller parameters is chosen as θ(0) = [0.5, 0, 0, 0] [T]. The conventional model reference adaptive controller is designed by using the equations (6) and (8). The simulations are done for the conventional MRAC and neural network-based MRAC system with random noise disturbance and nonlinear component are added to the plant. The simulation was carried out with MATLAB and the input is chosen as r(t)=21sin0.7t+25cos5.9t. The results for both conventional and proposed MRAC are given in fig 6.
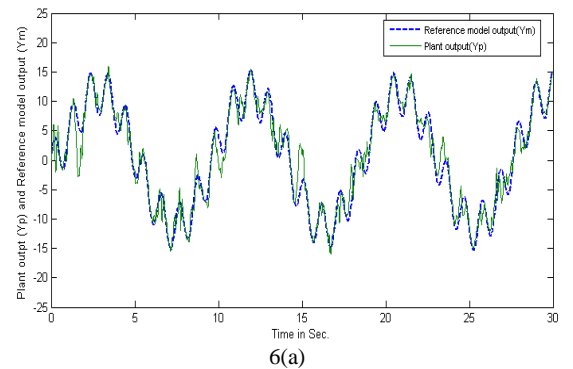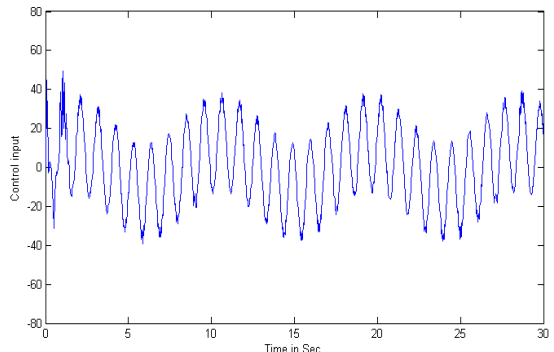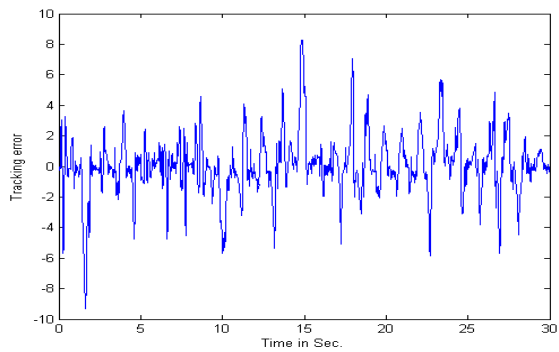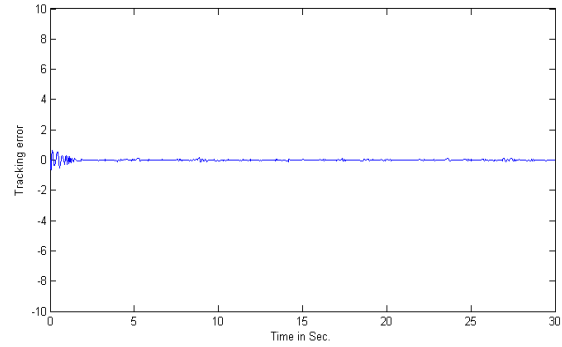

6(a)
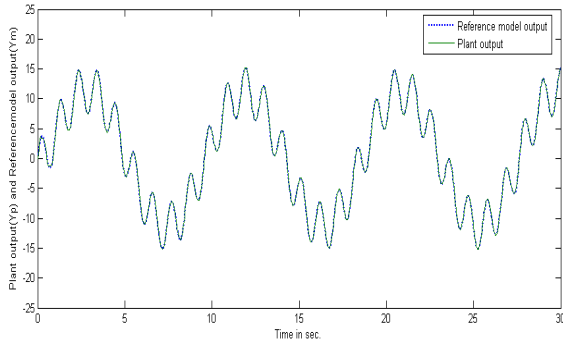
6(b)
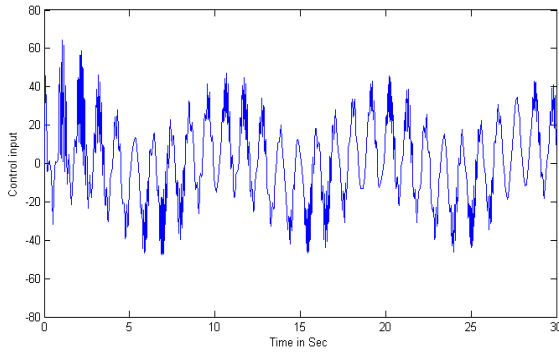
6(c)

6 (d)

6 (e)

6(f)

Fig. 6 Simulation Results: 6(a) Plant output y(t) (solid lines) and the Reference output y_m(t)(dotted lines) of the conventional MRAC system for the input r(t)=21sin0.7t+25cos5.9t. 6(b) Plant output y_p(t) (solid lines) and the Reference model output y_m(t) (dotted lines) of the proposed intelligent MRAC scheme for the input r(t)=21sin0.7t+25cos5.9t. 6(c) Control input of the conventional MRAC system.6 (d) Control input of the proposed intelligent MRAC system.6 (e) tracking error *e* for the conventional MRAC and 6(f) tracking error *e* for the proposed MRAC.

Example 2:

In this example, the nonlinearity of Dead Zone is followed by linear system. The disturbance (random noise signal) is also added to the input of the plant

Consider a second order system with the transfer function.

$$G\ (S) = \frac{5}{S^{2} + 10\,S + 25}$$

The reference model is taken as,

$$G_{M}\ (S) = \frac{1}{S^{2} + 3S - 10}$$

The simulation was carried out with MATLAB and the input is chosen as r(t)= 12. The initial value of the conventional MRAC scheme controller parameters is chosen as θ(0) = [3, 18,-8, 3] ^{T}. The conventional model reference adaptive controller is designed by using the equations (9) and (11). The results for both conventional and proposed MRAC are given in Fig. 7.
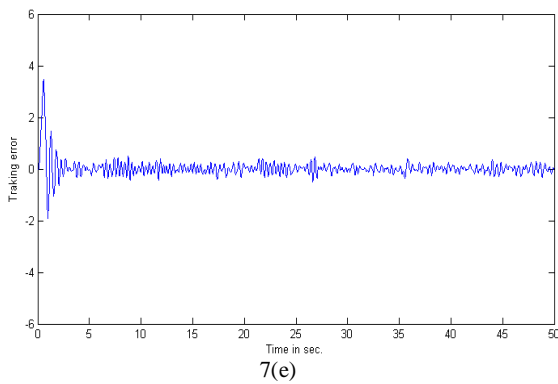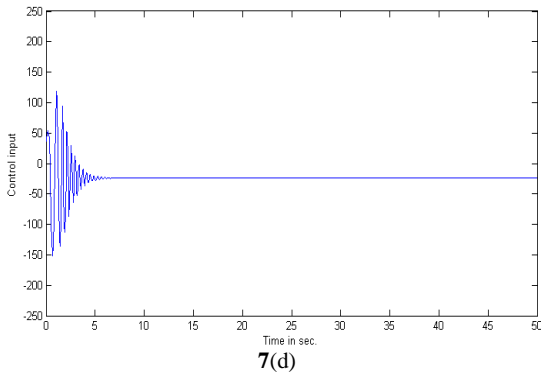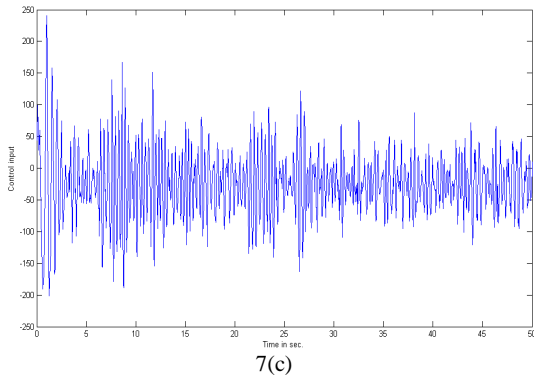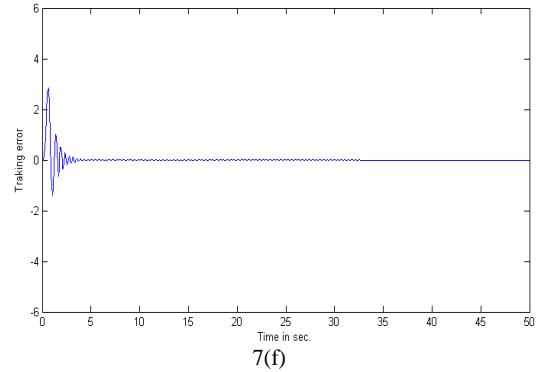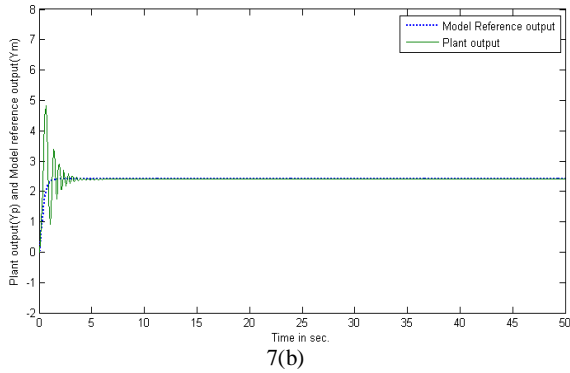

7(a)

7(b)

7(c)

7(d)

7(e)

7(f)
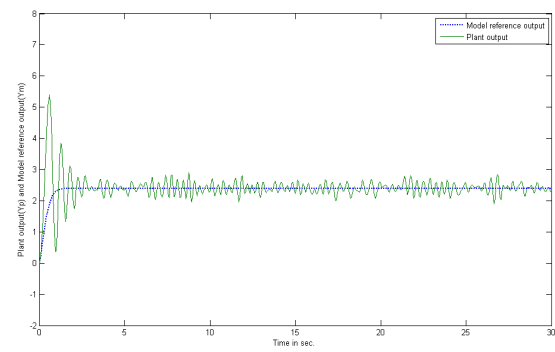
Fig. 7 Simulation Results: 7(a) Plant output $y_p(t)$ (solid lines) and the Reference output y_m (t) dotted lines) of the conventional MRAC system for the step input r(t)=12. 7(b) Plant output $y_p(t)$ (solid lines) and the Reference output $y_m(t)$ (dotted lines) of the proposed intelligent MRAC scheme for the step input r(t)=12. 7(c) Control input of the conventional MRAC system. 7(d) Control input of the proposed intelligent MRAC system.7 (e) tracking error *e* for the conventional MRAC and 7 (f) tracking error *e* for the proposed MRAC.

The nonlinear component and the disturbance (random noise signal) are added to the plant input of conventional MRAC. The plant output is not tracked with the reference model output and large amplitude of oscillations occur at the entire plant output signal as shown in fig 6(a) and 7 (a) and tracking error has not come to zero as shown in fig 6(e) and 7(e). When the disturbance (random noise signal) and non linear component are added to the input of the plant of the proposed neural network-based MRAC scheme, the plant output has tracked with the reference model output as shown in fig 6(b) and 7(b). The tracking error becomes zero within 4 seconds with less control effort as shown in fig 6(f) and 7(f) and no oscillation has occurred.

From the plots, one can see clearly that the transient performance, in terms of the tracking error and control signal, has been significantly improved by the proposed MRAC using neural network. The proposed neural network-based MRAC schemes show better control results are compared with those by the conventional MRAC .On the contrary, the proposed method has much less error than conventional method in spite of nonlinearities and disturbance.

6. Conclusion

In this section, the response of the conventional model reference adaptive controller is compared with the proposal model reference adaptive controller using neural network. The controller is checked with the two different plants. The proposed neural network-based MRAC controller shows very good tracking results when compared with the conventional MRAC. Thus the proposed intelligent MRAC controller modifies its behavior in response to the variation in the dynamics of

the process and the characteristics of the disturbances. The proposed scheme utilizes a growing dynamic neural network controller in parallel with the model reference adaptive controller. Simulations and analyses have shown that the transient performance can be substantially improved by proposed MRAC scheme and also the proposed controller shows very good tracking results when compared to conventional MRAC. Thus the proposed intelligent parallel controller is found to be extremely effective, efficient and useful.

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