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STABILITY ANALYSIS OF BRUSHLESS DC MOTOR SPEED CONTROLLERS DESIGN

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Abstract-All-coefficient adaptive control theory and method based on characteristic models have already been applied successfully in the fields of astronautics and industry. However, the stability analysis of the characteristic model-based Brushless DC Motor (BLDC) motor speed control systems is still an open question in both theory and practice. To investigate such stability issues, the author first provides a method for choosing initial parameter values and new performances for a projection algorithm with dead zone for adaptive parameter estimation, and develops some properties of time-varying matrices by utilizing some algebraic techniques. And then a new Lyapunov function with logarithmic form for time-varying discrete systems is constructed. Finally, the author transforms the characteristic models of some multi-input and multi-output (MIMO) controlled systems into their equivalent form, and proves the stability of the closed-loop systems formed by the golden-section adaptive control law based on the characteristic model using mathematical techniques.

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 modelling, nonlinearities and uncertainties. Model Reference Adaptive Control (MRAC) is one of the main schemes used in Brushless DC Motor (BLDC) system. Recently Model Reference Adaptive Control has received considerable attention, and many new approaches have been applied to practical process. In the MRAC scheme, the controller is designed to realize plant output converges to reference model output based on assumption that plant can be liberalized. Therefore this scheme is effectively for controlling linear plants with unknown parameters. However, it may not assure for controlling nonlinear plants with unknown structure. In recent years, an 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 next. A robust Adaptive control of uncertain nonlinear system using neural network is discussed earlier. Various types of NN have been efficiently utilized in identification of nonlinear systems. 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 as to minimize the output error between the NN's output and the observed output. The back propagation algorithm for efficiently updating the weight is useful in many applications such identification of non linear systems. Off-line iterative algorithm can be employed in such care of identification or modelling. However, in the aspect of control, the NN should work in on line 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 Kawalo presented a simple structure of NN based feed forward controller which is equivalently an inverse of the controlled system after the NN completes learning of the weights which are adjusted to minimize the feedback error. Narendra has shown in general indirect approach to nonlinear discrete time neuro – control scheme which consists of identification and adaptive control by using the NN Chen, and Liu that the NN – based adaptive control algorithm can cooperate well with identification of the nonlinear functions to realize a nonlinear adaptive control when the non linear adaptive control when the nonlinear control scheme is feedback linearizable. Kamalasudan 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. In particular, the adaptive tracking control architecture proposed in evaluated 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 discusses a direct adaptive neural network controller for a class of non linear system. In this paper a proposed MRAC 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

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matching for the uncertain linearized system to a given reference model. The network weights are adjusted by multilayer back propagation algorithm which 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 II proposes the problem statement and section III discusses the structure of an MRAC design. Section IV describes the proposed approach .Section V analysis the result and discussion of the proposed scheme and the conclusions are given in section VI. 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

Consider a SISI, 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 up is the plant input and yp 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 ym are the model's input and output. Define the output error as

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

Now the objective is to design the control input u such that the output error, e goes to zero asymptotically for arbitrary initial condition, where the reference signal r(t) is piecewise continuous and uniformely bounded.

Assumptions:

$Z_p(s)$ is a monic Hurwitz polynomial of degree mp

An upper bound n of the degree np of RP(s)

The relative degree $n^*=n_p-m_p$ of G(s)

The sign of the high frequency gain Kp are known

$Z_m(s),R_m(s)$ are monic Hurwitz polynomials of degree q_m, p_m respectively, where $p_m \quad \leq\ n$

The relative degree $n_m^*=p_{m-}q_m$ of $G_m(s)$ is the same as that of $G(s)$, i.e., $n_m^*=n^*$

3. STRUCTURE OF AN MRAC DESIGN

Relative Degree n =1

As in Ref [4] the following input and output filters are used,

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

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 $\omega=[\omega_1^T,\omega_2^T,y_p,r]^T$ (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 $P^*=\frac{k_p}{k_m}$ 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

$$\dot{\theta}=-\Gamma e_1\omega\,\mathrm{sgn}\left(p^*\right) \tag{8}$$

where Γ is a positive gain.

Relative Degree n =2

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

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

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

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

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 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

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

where e1= yp-ym and Γ is a positive gain

4. PROPOSED APPROACH

he block diagram of the proposed MRAC with neural network as shown in fig.1. The theoretical basis for the proposed scheme is as follows,

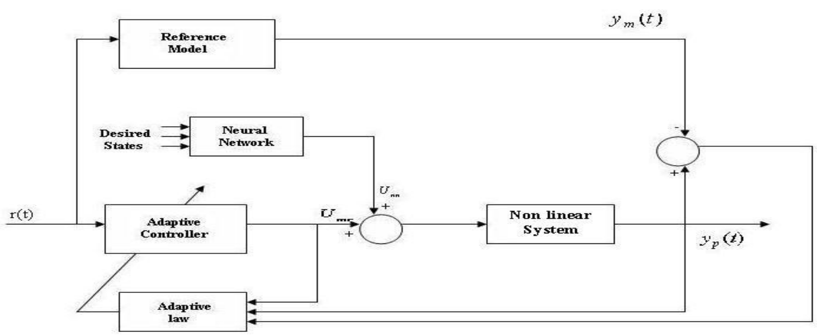


Fig 1. Block diagram of the proposed MRAC

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

$$X(t) = AX(t) + BU(t)$$
$$Y(t) = CX(t) + DU(t) \tag{12}$$

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 yp converges to the reference model output ym, we synthesize the control input U by the following equation,

$$U = U_{mr} + U_{nn} \tag{13}$$

where Umr is the output of the adaptive controller

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

Stability of the system and adaptability are then achieved by an adaptive control low Umr tracking the system state x 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.Thus it possible to have a system response equals to desired value if the controller Ud can effectively inverse the system dynamics. In otherwords the controller U should 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

$$U = c^{-1}(\dot{x}_{2d} - ax_1 + bx_{2d}) + U_{mr} \tag{15}$$

The neural network control law now becomes

$$U_d = D^{-1}(y_p, x_{2d}, \dot{x}_{2d}) \tag{16}$$

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

$$X = [y_p, x_{2d}, \dot{x}_{2d}] \tag{17}$$

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

5. STRUCTURED OF PROPOSED BLDC - 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. The multilayer back propogation networks is especially useful for this purpose, because of its inherent nonlinear mapping capabilities, which can deal effectively for real-time online computer control[16].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.

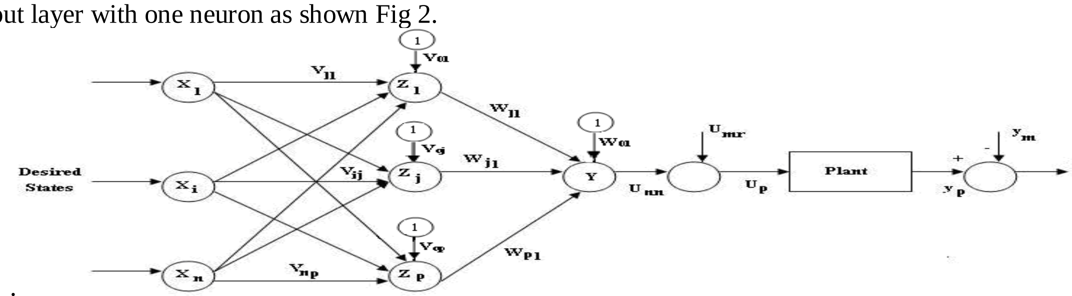


Fig 2.Structure of Neural Network

Let xi be the input to the i th node in the input layer, zj be the input to the j th node in the hidden layer, y be the input to the node in the output layers. Furthermore Vij be the weight between the input layer and hidden layer Wj1 be the weight between the hidden layer and the output layer. The input Xi to NN is given by $X_i = \{y_p, x_{2d}, \dot{x}_{2d}\}$

Learning of NN

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

$$Z_{-inj} = V_{oj} + \sum_{i=1}^{n} x_i V_{ij} \tag{18}$$

$$Y_{-ink} = W_{01} + \sum_{j=1}^{P} z_j W_{j1} \tag{19}$$

$$Z_j = F(Z_{-inj}) \tag{20}$$

$$Y_k = F(Y_{-ink}) \tag{21}$$

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

$$W_{j1}(new) = W_{j1}(old) + \Delta W_{j1} \tag{22}$$

$$W_{01}(new) = W_{01}(old) + \Delta W_{01} \tag{23}$$

$$V_{ij}(new) = V_{ij}(old) + \Delta V_{ij} \tag{24}$$

$$V_{0j}(new) = V_{0j}(old) + \Delta V_{0j} \tag{25}$$

The structure of proposed multilayer back propagation neural network controller design is represented in the form of flowchart as shown in fig 3.

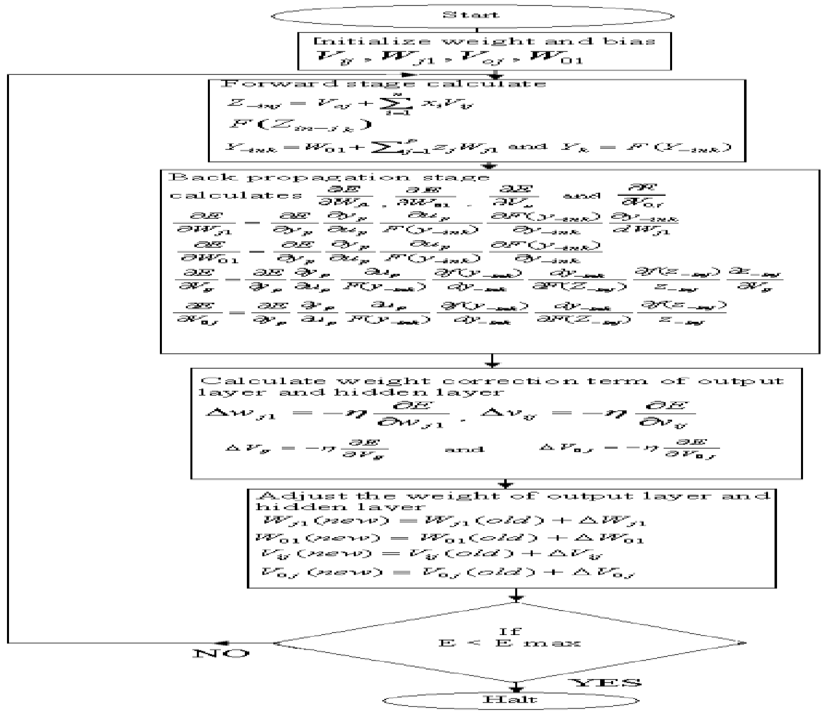


Fig 3.Proposed BPT Algorithm flow chart

6. RESULTS AND DISCUSSION

In this section, result of computer simulations for Conventional MRAC and the proposed intelligent MRAC method is reported. The results show the effectiveness of the proposed intelligent MRAC scheme and reveal its performance superiority to the Conventional MRAC technique. The simulink model of the proposed intelligent MRAC developed is given in fig .4

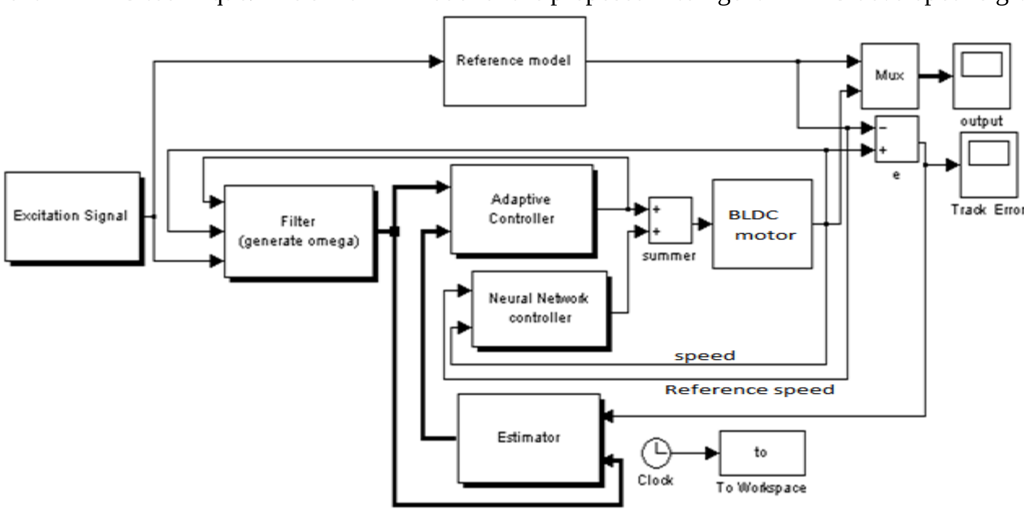


Fig. 4. Simulink Model of the proposed BLDC Motor Speed controller system

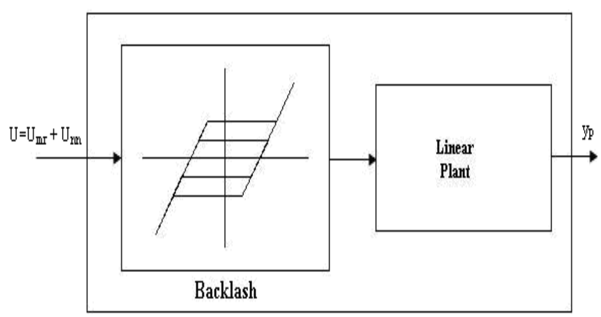


Fig.5 Non linear System

where β is the side-slip angle,yr is the yaw-rate,, p is the roll rate,Φ is the roll angle, y is the system output which is the yaw rate in this case, and u is the control input vector .From the data provided in horizontal flight at 40,000 ft and nominal forward speed 774 ft/s, the Boeing 747 lateral perturbation dynamics matrices are as follows:

The transfer function for the Lateral Dynamic Model of a Boeing 747 airplane System is given by

$$A = \begin{bmatrix} -0.0558 & -0.9968 & 0.0802 & 0.0415 \\ -0.598 & -0.115 & 0.0318 & 0 \\ -3.05 & 0.388 & -0.465 & 0 \\ 0 & 0.0805 & 1 & 0 \end{bmatrix}$$ assume that the linear part of the controlled system and the

$$b = \begin{bmatrix} 0.01 \\ -0.5 \\ 0.2 \\ 0 \end{bmatrix}$$

reference model are given by, $$G(s) = \frac{-0.5s^3 - 0.2608s^2 - 0.1223s - 0.05832}{s^4 + 0.6358s^3 + 0.9389s^2 + 0.5116 + 0.003674}$$

$$G_m(s) = \frac{1}{(s+3)}$$

The simulation was carried out with MATLAB and the input is chosen as r(t)=30sin0.7t.
The results for both conventional and proposed MRAC are given in Figure 6. The proposed intelligent MRAC schemes better control results compared to those by the conventional MRAC.

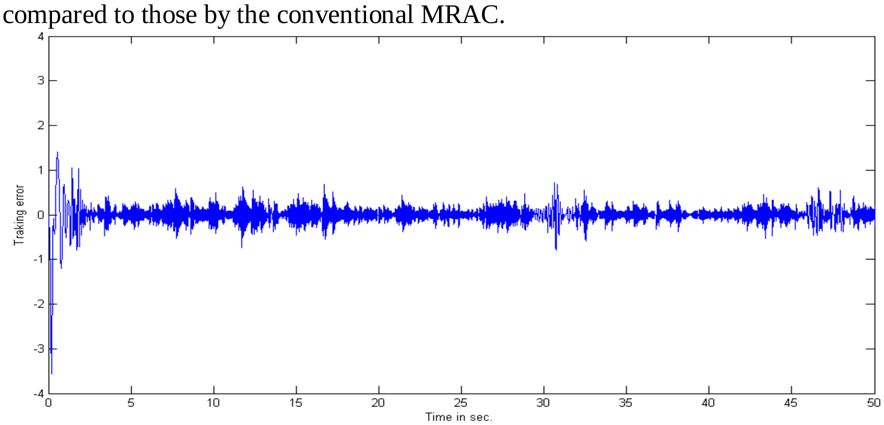
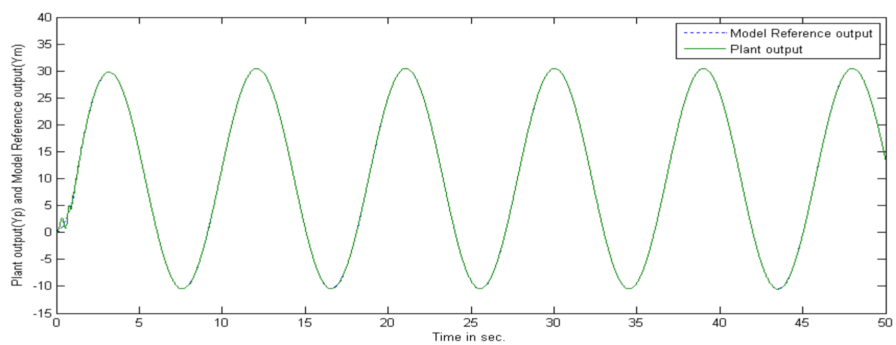


Figure 6 (e) Tracking error e for the conventional MRAC

Figure.7 (a) Plant output yp(t) (solid lines) and the Reference output ym (t) (dotted lines) of the conventional MRAC system for the input r(t)= 10+25sin0.7t



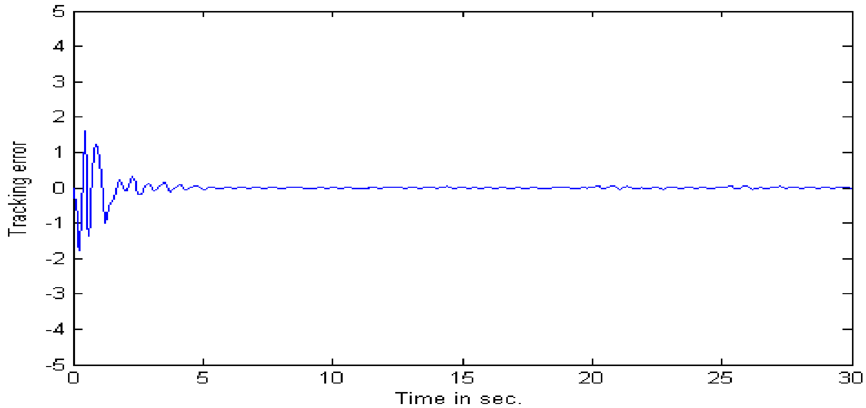


Figure 9 (e) Tracking error e for the conventional MRAC

7. 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 different plants. The proposed MRAC controller using neural network shows very good tracking results when compared with the conventional MRAC. Thus the proposed intelligent control effort.

MRAC controller modifies its behavior in response to the variation in the dynamics of the process and the characteristic of the disturbances. Proposed scheme utilizes a growing dynamic neural network controller in parallel with the model reference adaptive controller. Simulations and analyses have been 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 found to be extremely effective and efficient.

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