Adaptive controller for improved performance of brushless DC motor

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Leena Nair
NSS College of Engineering

Adaptive Controller for Improved Performance of Brushless DC Motor

N. Leena, *Member, IEEE*, R. Shanmugasundaram, *Member, IEEE*

Abstract— **This paper presents the development and performance analysis of model reference adaptive controller using Artificial Neural Network (ANN) for Brushless DC motor (BLDC) drives. The model reference adaptive systems (MRAS) have a parameter adjustment mechanism along with the normal feedback loop and hence give better solutions when there are variations in process parameters. Neural networks (NNs) with their inherent parallelism, learning capabilities and fault tolerance have proven to be a promising solution in estimating and controlling nonlinear systems. This paper combines a MRAS with ANN to solve the problems of non-linearity, parameter variations and load excursions that occur in BLDC motor drive systems. The performance of the traditional PID controller based speed control method is compared with the model reference based speed control for BLDC motor drive system using MATLAB Simulink software. Simulation results are presented to prove that the MRAC based model is capable of speed tracking as well as reduce the effect of parameter variations.**

Index Terms— **Artificial neural network (ANN), Brushless DC Motor, Model reference adaptive control (MRAC), PID controller.**

I. Introduction

The industrial world of today is fast growing and so is the demand for precision. There are several applications today that demand high performance. Among the various motors, brushless dc motors are gaining widespread popularity in HVAC industry, medical equipment's, electric vehicles, aerospace, military equipment's, hard disk drives, due to its well-known advantages like high efficiency, high power factor and low maintenance.

The conventional controllers used in high performance drives are proportional integral (PI) or proportional integral derivative (PID). These are constant gain controllers and require accurate mathematical models or system response for their design. The BLDC motor drive is highly non-linear. It is often very difficult to obtain an accurate mathematical model for the motor using the conventional techniques. Furthermore, the properties of the motor are usually unknown and time-varying. The conventional controllers fail to give optimal performance during such changes in operating conditions like variations in load, saturation, changes in parameters or noise propagations. This has resulted in an increased interest in intelligent and adaptive controllers.

One of the major approaches to adaptive control is Model Reference Adaptive Control (MRAC).The objective is to design a controller with adjustable parameters so that the behavior of the plant to be controlled follows a desired behavior in spite of variations in plant parameters or other uncertainties'.

Artificial Neural Network "ANN" has been applied successfully to a wide range of control system applications in recent years. Artificial neural networks have high learning and nonlinear mapping essences and its parallel and distributed structure can provide a nonlinear mapping between inputs and outputs of an electric drive system, without the knowledge of any predetermined model. This makes ANN a good choice to be used in the adaptation mechanism of a MRAC system.

In the proposed work, a speed control strategy for BLDC motor is proposed using a model reference adaptive controller based on Artificial Neural Networks. The performances of the proposed drive system and the conventional PID control are evaluated at different operating conditions, such as sudden load impact, parameter variations, etc.

The information gathered from the literature to carry out this work is as follows. The modeling of brushless dc motor is discussed in [2], [3].The effect of changes in motor parameters and load disturbances on the performance of a brushless dc motor drive are presented in [4],[5]. Several tuning methods for PID controllers are described in [7]-[9].The tuning method suggested in [9] is found to yield optimum performance and is adapted in this work to determine PID controller gain parameters. Robust and adaptive speed control of motor drives using ANN based speed controllers are reported in [14]-[17], [19].

II. BLDC Motor Drive Dynamics

To design the artificial neural network based adaptive controller for BLDC motor drive, the modeling of BLDC motor is essential. The mathematical model of BLDC motor is represented in the form of mathematical equations. The BLDC motor drive system can be described by the following equations:

N.Leena is working as Assistant Professor in theElectrical and Electronics Engineering Department of Federal Institute of Science and Technology,Angamaly-683577, India (e-mail: lee_eee02@yahoo.co.in).

R.Shanmugasundaram is working as Assistant Professor in Electrical and Electronics Engineering Department of Sri Ramakrishna Engineering College, Coimbatore-641022, India (e-mail: rss_is@yahoo.com).

$$V_a = R_a i_a + L_a \frac{di_a}{dt} + k_b \omega_m \quad (1)$$

$$V_b = R_b i_b + L_b \frac{di_b}{dt} + k_b \omega_m \quad (2)$$

$$V_c = R_c i_c + L_c \frac{di_c}{dt} + k_b \omega_m \quad (3)$$

$$T_e = k_t i = J \frac{d\omega_m}{dt} + B\omega_m + T_l \quad (4)$$

where R_a, R_b, R_c are the per phase resistance of phase a, b and c respectively, L_a, L_b, L_c are the per phase self-inductance of phase a, b and c respectively, ω_m is the rotor speed, V_a, V_b, V_c is the per phase voltage and $i = i_a = i_b = i_c$ are the phase current of phase a, b and c respectively, T_e and T_l are electromagnetic torque developed by the motor and load torque, J and B are inertia and friction coefficients.

Assuming the load to be a fan or propeller load, the relation between the load torque and speed can be described by the following relation:

$$T_l = \mu(\omega_m)^2 \quad (5)$$

where μ is a constant used for modeling the nonlinear mechanical load.

Equations (1)-(3) are combined and continuous quantities replaced by finite difference equations to get,

$$\omega_m(k+1) = \alpha\omega_m(k) + \beta\omega_m(k+1) - \gamma\omega_m^{\,2}(k) + \delta\omega_m^{\,2}(k-1) + \varsigma V(k) \quad (6)$$

where α, β, γ, δ and ζ are constants that can be expressed in terms of the motor parameters. Equation (4) can be further modified to obtain the inverse dynamic model of the drive system as:

$$V(k) = f(\omega_m(k+1), \omega_m(k), \omega_m(k-1)) \quad (7)$$

Thus it can be seen that the control voltage is a non-linear function of three consecutive samples of motor speed. In the above equation, one sample of predicted speed $\omega_m(k+1)$is replaced by one sample of reference speed. The ANN can learn this non-linearity between input and output

III. PID CONTROLLER

A. Conventional control schemes of BLDC motor

The conventional controllers used for robust control are mainly constant gain controllers, such as proportional integral (PI) or proportional integral derivative (PID). The idealized equation of a proportional-integral-derivative (PID) controller is

$$u(t) = K\left(e(t) + \frac{1}{T_i}\int_0^t e(t)dt + T_d \frac{de(t)}{dt}\right) \quad (8)$$

where K is the proportional constant, Ti is the integral time, Td is the derivative time, and e(t) is the error; i.e., e(t) =r(t) – y(t) where r(t) is the reference input and y(t) is the output.. The equivalent transfer function in the s-domain is given by

$$u(t) = K\left[1 + \frac{1}{T_i s} + T_d(s)\right]E(s) \quad (9)$$

The PID controller shows a smaller maximum overshoot and has no steady state error due to the integral action.

B. Simulation of PID control scheme for BLDC motor

Fig.1 shows the MATLAB/ Simulink model of BLDC motor with PID controller. The most popular design technique for PID controllers is Ziegler-Nichols method, which relies solely on parameters obtained from the system step response. In this paper, the PID controller is designed according to the method in [9] which also relies solely on parameters obtained from plant step response. The values of Kp, Ki and Kd calculated are 0.03, 0.0029 and 0.0024 respectively for the motor parameters given in Appendix.

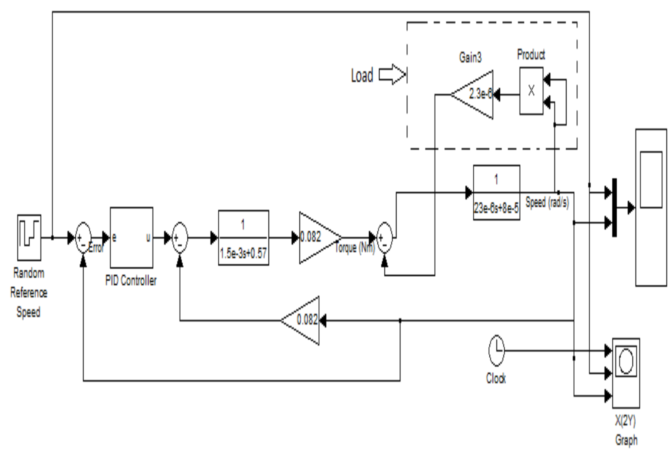

Fig.1 Simulink model of BLDC motor with PID controller

The system response obtained under different operating conditions like change in reference speed, change in inertia and change in phase resistance for the load in (5) are shown in Fig.2-Fig.4. Fig.2 shows the speed response for a step change in reference speed when the resistance value is doubled. It can be seen that the system takes 30ms to reach steady state with a percentage overshoot of 7% and zero steady state error.

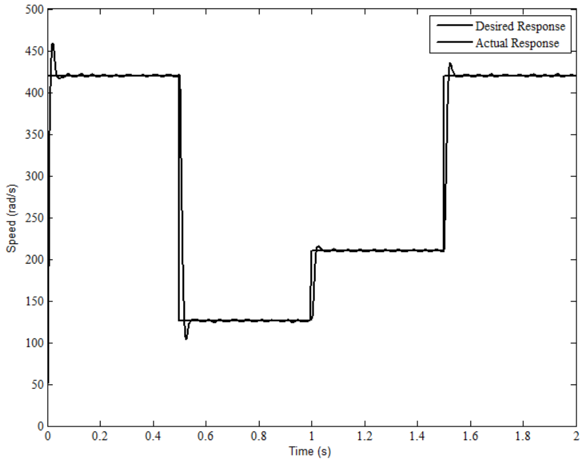

Fig. 2. Speed response of PID control system with step change in reference speed and change in resistance(R to 2R)

Fig.3 shows the speed response for step change in reference speed with an increase in inertia. It can be seen that an increase in inertia from J to 2J increases the settling time to 50ms with a percentage overshoot of 10% and zero steady state error.

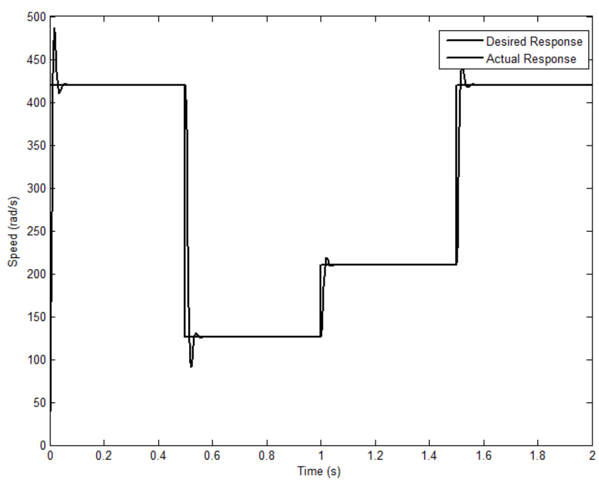

Fig.3 Speed response of PID control system with step change in reference speed and change in inertia (J to 2J)

The speed response of the system with step change in reference speed and an increase in resistance and inertia to double the initial values are shown in Fig.4. It can be seen that the system response is slightly sluggish with a settling time of 80ms and a maximum overshoot of 23% and a steady state error of 1rad/s.

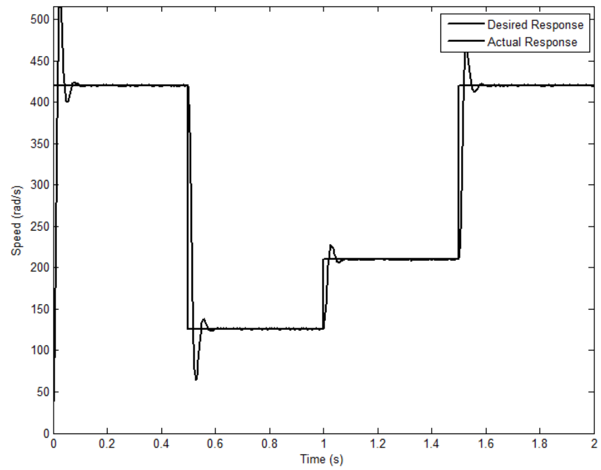

Fig.4 Speed response of PID control system with step change in reference speed and change in parameters (R to 2R and J to 2J)

It can be seen that the PID controllers can produce satisfactory results for fixed parameter system. However in practical systems, system parameters change during working. Hence there is a need to find alternative control strategies like neural controllers or fuzzy controllers to achieve the desired performance.

IV. ADAPTIVE CONTROL OF BLDC MOTOR

A. Model Reference Adaptive Control

Artificial neural network has self-learning and self-regulatory capability and are widely used for identification and control of non-linear systems. The most fundamental neural network based controllers are probably those using the "inverse" of the process as the controller called direct inverse control. Another technique is known as model reference adaptive control (MRAC) and is widely used for control of non-linear systems. It has the advantage that the plant response can be driven towards a reference model response which gives the desired transient behavior. The architecture of model reference adaptive controller is shown in Fig.5.

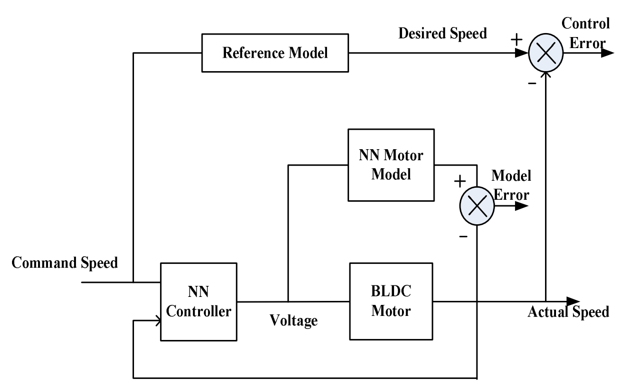

Fig.5 Model reference controller architecture

B. Simulation of Model reference adaptive controller

The simulation of MRAC controller is carried out using the Neural Networks Toolbox of MATLAB. This neural controller has two neural networks; one is used to model the system and is called the plant identifier and the other acts as the controller. The identifier is a multi-layer neural network with a back-propagation learning scheme. The controller is a recurrent learning multilayer neural network. Using the measured values from the plant, the identifier is trained offline. This block estimates the behavior of the plant and its output is used to generate model error as shown in Fig.5. The controller is then trained so that the system response follows that of the reference model (input to the system).The reference model chosen is that of BLDC motor with PID controller which is fine tuned to give optimum response. The BLDC model is shown in Fig.6.

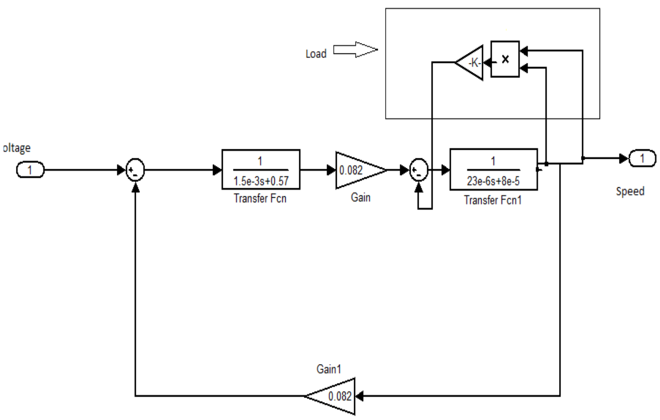

Fig.6 BLDC motor model

The magnitude of the error for the plant identification was of the order of 10e-9. The plant identifier network has one delayed input and two delayed outputs and ten hidden layers. Ten thousand samples are used for the one thousand epochs of training. The Levenberg-Marquardt algorithm is used for the training of the plant model. The controller training is trained after the plant identification. The BFGS (Broyden, Fletcher, Goldfarb, and Shanno) Quasi–Newton training algorithm is adopted here and the performance (magnitude of error) is of the order of 10e-6. A network with thirteen hidden layers and one delayed input and two delayed outputs, is chosen as the neural network controller.

After the controller training is completed the results obtained to evaluate the learning capability of the controller is shown in Fig.7. The plant response clearly shows that the neural network output clearly follows the response of the reference model (desired output).

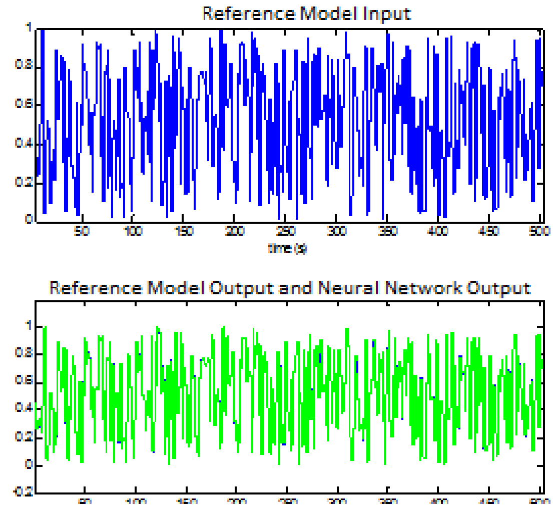

Fig.7 Performance of the neural network model reference controller after training.

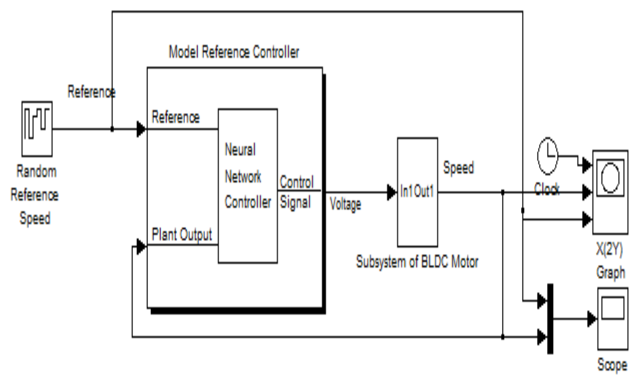

Fig.8 MATLAB /Simulink model of BLDC motor with MRAC controller

The system response as obtained under different operating conditions like change in reference speed, change in inertia and change in phase resistance and are shown in Fig.9-Fig.11. Fig.9 shows the speed response for a step change in reference speed when the resistance value is doubled. It can be seen that the system takes 12ms to reach steady state with a no overshoot and zero steady state error.

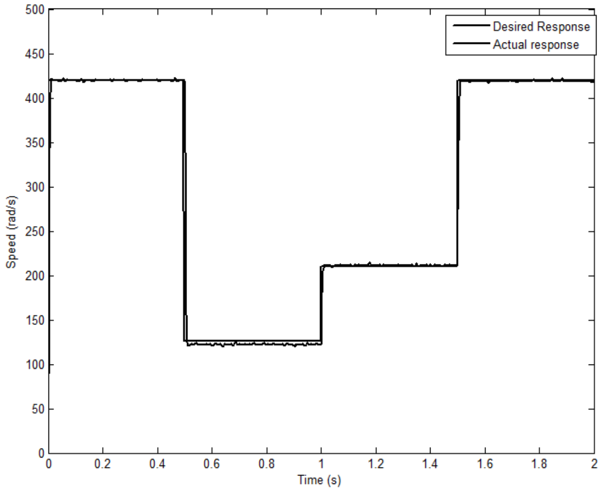

Fig.9 Speed response of a MRAC system with step change in reference speed and change resistance(R to 2R)

Fig.10 shows the speed response for a step change in reference speed with an increase in inertia. It can be seen that an increase in inertia from J-2J increases the settling time to 24ms with a percentage overshoot of 8.3% and steady state error of 2.5 rad/s.

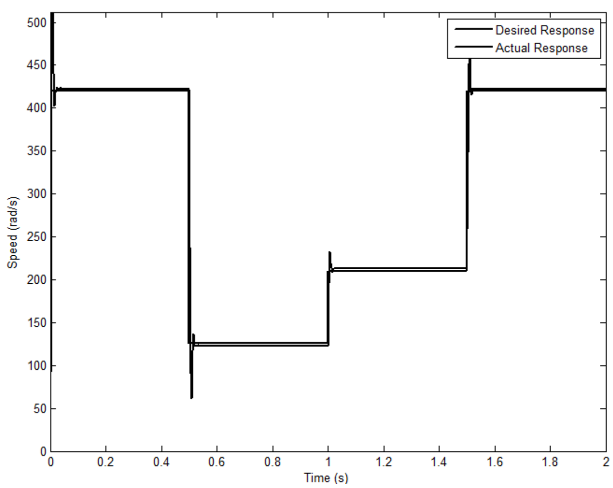

Fig.10 Speed response of a MRAC system with step change in reference speed and change in inertia (J to 2J)

The speed response of the system to step change in reference speed with an increase in resistance and inertia to double the initial values are shown in Fig.11. It can be seen that the system response is slightly sluggish with a settling time of 40ms with no overshoot or steady state error.

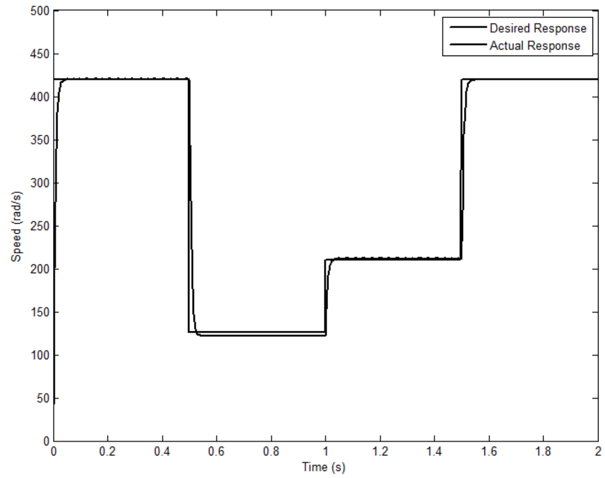

Fig.11 Speed response of a MRAC system with step change in reference speed and change in resistance and inertia (R to 2R and J to 2J)

V. RESULTS AND DISCUSSION

The simulation studies clearly show that a neural network based model referenced control algorithm improves transient and steady state behavior of BLDC motor over classical PID control technique. The PID and Model reference adaptive controllers are both able to track the changes in reference speed. However the MRAC technique performs better than the PID controller during system parameter changes and is able to track reference speed more accurately.

TABLE 1
PERFORMANCE PARAMETERS OF PID AND MRAC CONTROLLER

Performance Measures		Settling time ts (sec)	Maximum Percentage Overshoot (%)	Steady State Error (rad/s)
Changes in operating conditions	Controller			
Change in reference speed with change in resistance (R to 2R)	MRAC	0.012	Zero	Zero
	PID	0.03	7	Zero
Change in reference speed with change in inertia (J to 2J)	MRAC	0.024	8.3	2.5
	PID	0.05	10	Zero
Change in reference speed with change in resistance and inertia (R to 2R and J to 2J)	MRAC	0.04	Zero	Zero
	PID	0.08	23	1

From the table above, it can be inferred that BLDC drive employing Model Reference Adaptive Controller is able to respond with smaller settling time and lesser overshoot and steady state error than the one employing PID controller when there are changes in resistance or inertia or both along with changes in reference speed.

VI. CONCLUSION

The tuning effort of an MRAC based system is much less than that of a conventional PID system as it does not need the tuning of controller parameters for variations in plant parameters. From the simulation results, it can be seen that the MRAC based model is capable of speed tracking as well as reduce the effect of parameter variations. This makes the motor suitable in applications such as Position Sensing and Robotics. The proposed ANN-based control scheme is robust, efficient and easy to implement. The hardware implementation of the proposed system needs to be done to validate the capability of the MRAC controller to cope up with speed and other parameter variations.

APPENDIX

BLDC MOTOR SPECIFICATIONS

Rated speed	4000 rpm
Number of phases	3
Number of poles (P)	4
Rated current	5 A
Rated voltage	36 V
Per phase Resistance	0.57 ohms
Per phase Inductance	1.5mH
Moment of inertia (J)	23e-6kg-m^2
Rated Torque (T)	0.42N.m
Torque constant	0.082N.m/A

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