

## **Improvement in the Performance of Brushless DC Motor Control by ANN**

**D.Thandava Krishna, P.Jyosna**

M.Tech Student, Dept of EEE, SIETK, Puttur  
Asst.Prof, Dept of EEE, SIETK, Puttur, Andhra Pradesh.

### **ABSTRACT**

This project displays the improvement and execution investigation of model reference versatile controller utilizing Artificial Neural Network (ANN) for Brushless DC engine (BLDC) drives. The model reference versatile frameworks (MRAS) have a parameter change component alongside the typical input circle and henceforth give better arrangements when there are varieties in procedure parameters. Neural systems (NNs) with their inalienable parallelism, learning abilities and adaptation to internal failure have turned out to be a promising arrangement in evaluating and controlling nonlinear frameworks. This paper joins a MRAS with ANN to take care of the issues of non-linearity, parameter varieties and burden journeys that happen in BLDC engine drive frameworks. The execution of the customary PID controller based rate control strategy is contrasted and the model reference based pace control for BLDC engine drive framework utilizing MATLAB Simulink programming. Test results utilizing TMS320LF2407A is introduced to demonstrate that the MRAC based model is fit for rate following and also decrease the impact of parameter varieties

### **INTRODUCTION**

The modern universe of today is quickly developing as is the interest for accuracy. There are a few applications today that request superior. Among the different engines, brushless dc engines are increasing boundless fame in HVAC industry, medicinal equipment's, electric vehicles, aviation, military equipment's, hard plate drives, because of its surely understood focal points like high effectiveness, high power component and low maintenance. □The routine controllers utilized as a part of elite drives are corresponding necessary (PI) or relative basic subsidiary (PID). These are consistent increase controllers and require exact scientific models or framework reaction for their configuration. The BLDC engine drive is exceedingly non-straight. It is regularly exceptionally hard to get an exact scientific model for the engine utilizing the traditional methods. Moreover, the properties of the engine are normally obscure and time- differing. The ordinary controllers neglect to give ideal execution amid such changes in working conditions like varieties in burden, immersion, changes in parameters or commotion proliferations. This has brought about an expanded enthusiasm for smart and versatile controllers. One of the major ways to deal with versatile control is Model Reference Adaptive Control (MRAC).The goal is to plan a controller with movable parameters so that the conduct of the plant to be controlled takes after a sought conduct disregarding varieties in plant parameters or different vulnerabilities'. Manufactured Neural Network "ANN" has been connected effectively to an extensive variety of control framework applications as of late. Fake neural systems have high learning and nonlinear mapping forces and its parallel and dispersed structure can give a nonlinear mapping in the middle of inputs and yields of an electric commute framework, without the information of any foreordained model. This settles on ANN a decent decision to be utilized as a part of the adjustment system of a MRAC framework. In the proposed work, a rate control procedure for BLDC engine is proposed utilizing a model reference versatile controller taking into account Artificial Neural Networks. The exhibitions of the proposed ANN drive framework and the customary PID control are outlined and actualized utilizing TMS320LF2407A advanced sign processor and assessed under distinctive working conditions, for example, sudden burden sway, parameter varieties, and so forth. The data accumulated from the writing to complete this work is as per the following. The impact of changes in engine parameters and burden unsettling influences on the execution of a

*\*Address for correspondence:*

brushless dc engine drive is displayed furthermore a few tuning strategies for PID controllers are portrayed. The tuning strategy recommended is found to yield ideal execution and is adjusted in this work to focus PID controller addition parameters. Powerful and versatile rate control of engine drives utilizing ANN based pace controllers are accounted.

### 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:

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

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

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

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

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,  $\omega_m$  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  $\mu$  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,

$$\omega_m(k+1) = \alpha\omega_m(k) + \beta\omega_m(k+1) - \gamma\omega_m^2(k) + \delta\omega_m^2(k-1) + \zeta V(k) \quad (6)$$

where  $\alpha, \beta, \gamma, \delta$  and  $\zeta$  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.

The block diagram of the experimental set-up is given in Fig.1. It consists of an IGBT power inverter, sensing circuits, BLDC motor and the TMS320LF2407A digital signal processor. The low cost and hybrid power IC (IRMAY20UP60A) is used as the IGBT power inverter. This IC is designed for motor drive applications by International Rectifiers and replaces the conventional bulky and expensive individual inverter switches and their associated driver and isolation circuits. The built-in hall sensors of the BLDC motor generate three hall sensor signals corresponding to rotor position. The DSP controller generates the 20 kHz PWM signal using the Event manager A module components. This signal is AND ed with the hall sensor signals to generate gating signals for the IGBT switches. The high speed digital buffer IC 74HCT244 is used to interface the DSP with the hybrid power IC and the hall sensor circuit. The duty cycle of the PWM control signal produced by the controller is varied to vary the phase voltage to control the speed of the motor. The control algorithm for PID and neural network control are written using Code Composer Studio 3.0 software and the output file is downloaded from the personal computer to the DSP.

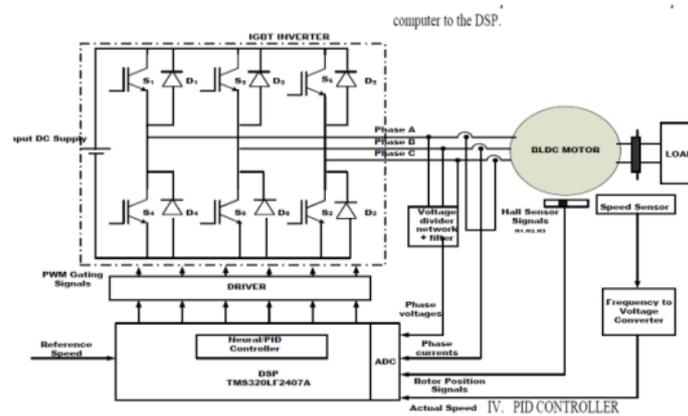


Fig.1 Block diagram of proposed model

The high speed digital buffer IC 74HCT244 is used to interface the DSP with the hybrid power IC and the hall sensor circuit. The duty cycle of the PWM control signal produced by the controller is varied to vary the phase voltage to control the speed of the motor. The control algorithm for PID and neural network control are written using Code Composer Studio 3.0 software and the output file is downloaded from the personal computer to the DSP.

### 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

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

Where K is the proportional constant,  $T_i$  is the integral time,  $T_d$  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 PID controller shows a smaller maximum overshoot and has no steady state error due to the integral action.

### IMPLEMENTATION OF PID CONTROL SCHEME FOR BLDC MOTOR

The most popular design technique for PID controllers is Zeigler-Nichols method, which relies on the parameters obtained from step response. In this paper, PID controller parameters are determined from [7]. The idealized equation for the continuous PID algorithm is

$$u(t) = K_p e(t) + K_i \int e(t) dt + K_d \frac{de(t)}{dt} \quad (9)$$

Where  $u(t)$  is the output of the PID controller at time  $t$ ,  $K_p$  is the proportional gain constant,  $K_i$  is the integral gain constant,  $K_d$  is the derivative gain constant, and  $e(t)$  is the error at time  $t$ . For small sample times the continuous time PID equation can be turned into a difference equation by discretization. The final discrete version of the PID equation then takes the form

$$u(k) = u(k-1) + k_1 e(k) + k_2 e(k-1) + k_3 e(k-2) \quad (10)$$

where  $u(k-1)$  is the previous control output,  $e(k-1)$  is the previous error, and  $e(k-2)$  is the error preceding  $e(k-1)$ . The new constants  $K_1$ ,  $K_2$ , and  $K_3$  are determined by

$$K_1 = K_p + \frac{TK_i}{2} + \frac{K_d}{T} \quad (11)$$

$$K_2 = -K_p - \frac{2K_d}{T} + \frac{TK_i}{2} \quad (12)$$

$$K_3 = \frac{K_d}{T} \quad (13)$$

$$T = \frac{1}{f} \quad (14)$$

Where  $f$  is the sampling frequency of the controller. PID algorithm implementation is achieved by using inbuilt ADC and Timer registers of the Event manager 1 module of the controller. The reference speed is set in the Code Composer studio. The actual speed is obtained using the Frequency to voltage converter and converted to digital value using the ADC module of the processor. The PID control algorithm is written for DSP using Code Composer Studio3 software and the output file generated is downloaded from personal computer to DSP. This program converts this error voltage into the required duty cycle and is given to the timer to produce a PWM signal that gives the required phase voltage. The system response obtained under different operating conditions like change in reference speed, change in inertia and change in resistance.

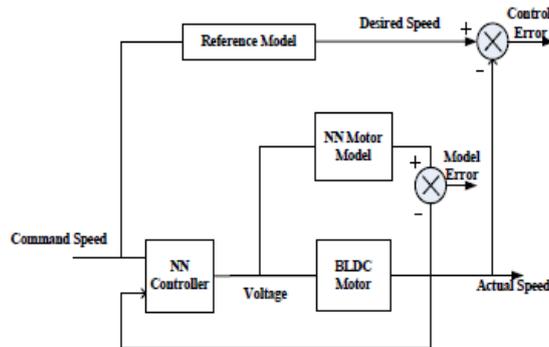
**ADAPTIVE CONTROL OF BLDCMOTOR**

**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 as shown in fig.

**B. Implementation of Model reference adaptive controller**

The first and foremost step in implementation of model reference adaptive control is the selection of reference model. Selection of the reference model dynamics is a very important part of the adaptive system design procedure that ultimately defines the desired system behavior. A model that gives the desired transient response specifications is usually taken as the reference model.



**Fig.2** Model reference controller architecture

In this work, a PID controller designed according to the method is taken as the reference model. It is found that this gives optimum transient response. The plant is made to emulate the characteristics of this PID controlled system. The second part is to generate the training data for offline training. From (7) it can be seen that control voltage is a nonlinear function of three samples of speed. It can be further modified to obtain the inverse dynamic model of the drive system as

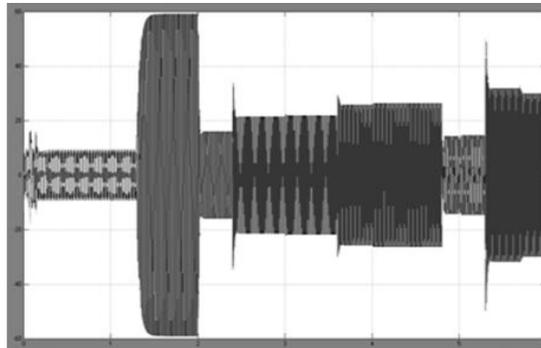
$$V(k) = f(\omega_m(k+1), \omega_m(k), \omega_m(k-1)) \tag{15}$$

In the above equation, one sample of predicted speed  $\omega_m(k+1)$  is replaced by one sample of reference speed  $\omega_{ref}(k+1)$ . The ANN is made to learn this non-linearity between voltage and speed. Hence an input matrix of  $[\omega_{ref}(k+1) \ \omega_m(k) \ \omega_m(k-1)]$  is formed. The output vector contains the duty cycle to produce the required voltage  $V(k)$ . Data for training can be obtained either by simulation or from experiment. Here data has been collected both in real time from a PID controlled BLDC motor system as well as by simulation from a Simulink model of the BLDC motor drive. The PID control algorithm is modified to capture steady state and transient data. The reference speed was varied in steps of three and both acceleration & deceleration and steady state data were obtained. 4500 samples of data are collected as shown in excel sheet. The collected data has been normalized to train the ANN. A

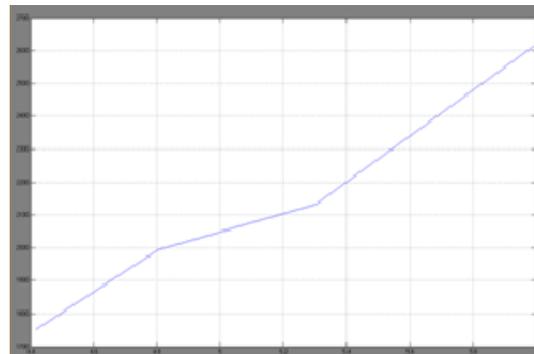
simulation model of the BLDC motor was set-up in Simulink to obtain training data from simulation. A sampling rate of 1.5ms was used to generate 501 samples of training data for different operating conditions. A back propagation algorithm is written in MATLAB to generate the final weights and bias matrices. Feed forward architecture with one hidden layer having 5 neurons is chosen and the learning rate and momentum factors chosen as 0.05 and 0.9 respectively. The ANN control algorithm was implemented in the DSP processor.

### **SIMULATION RESULTS**

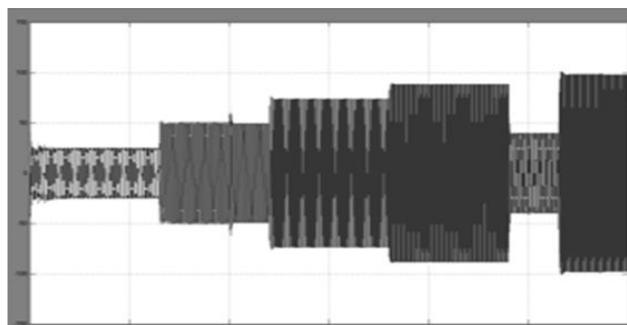
#### ***Proposed Method:***



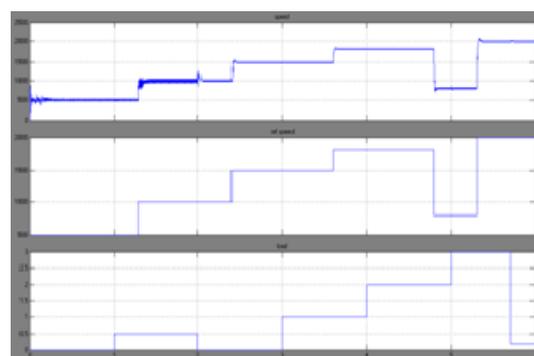
**Fig(a).** *Stator currents*



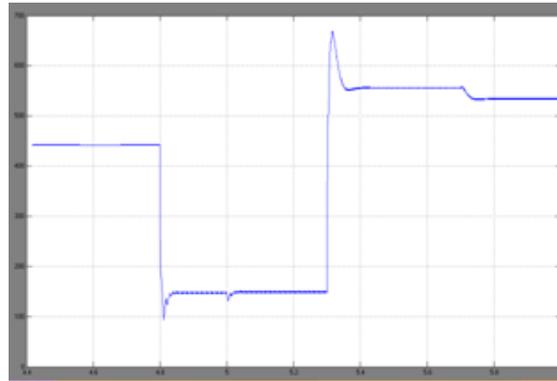
**Fig (b).** *Angle Theta*



**Fig(c).** *Rotor Emfs*



**Fig(d).** *Speed, Ref Speed, Torque*



Fig(e). VDC Voltage

**Extension Work:**

The performance of the Model Reference controller for BLDC motor drive has further improved by connecting with the cascaded PI controller to it and is successfully implemented using a simple ANN architecture. Therefore this scheme is robust, efficient than the proposed one.

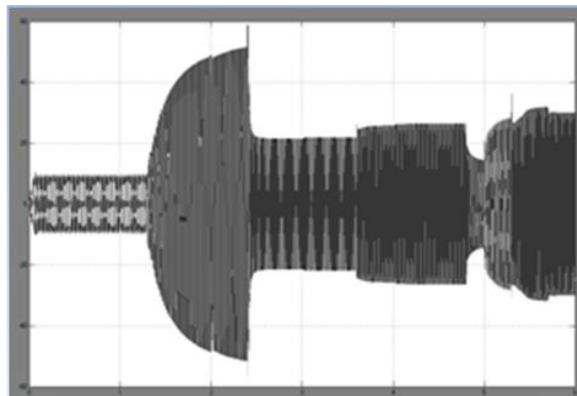


Fig (f). Stator currents

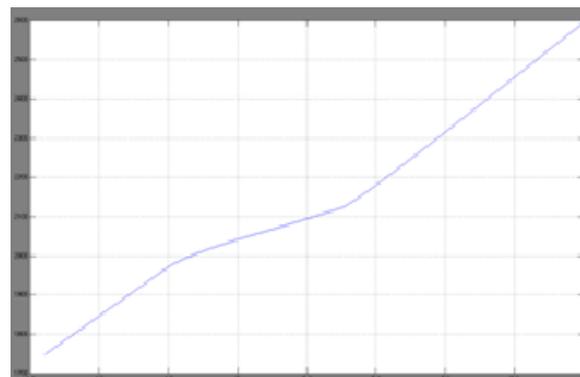


Fig (g). Angle Theta

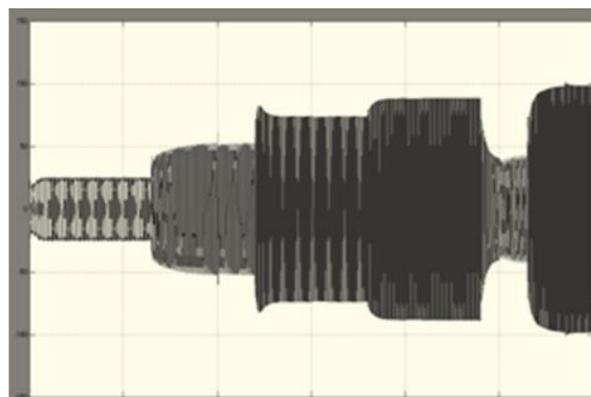


Fig (h). Rotor Emfs

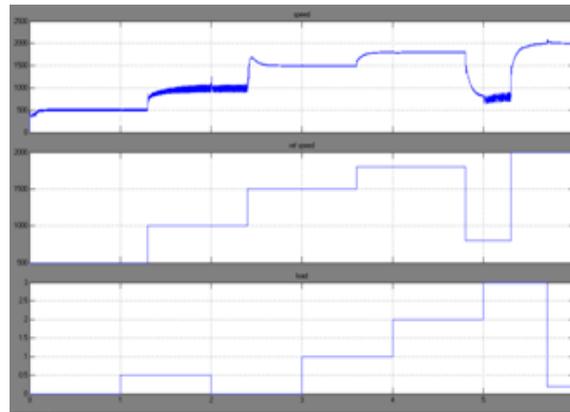
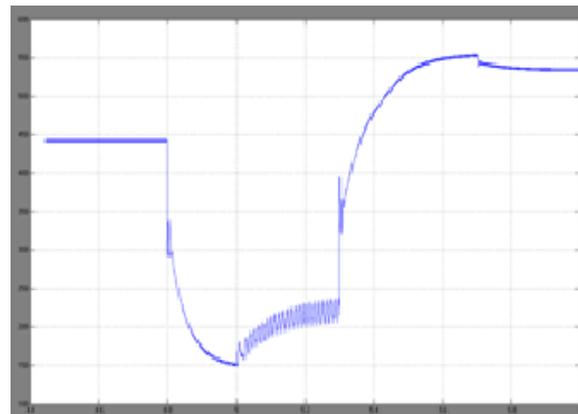


Fig (i). Speed, Ref Speed, Torque



Fig(j). VDC Voltage

## CONCLUSION

The Model Reference controller for BLDC motor drive is successfully implemented using a simple ANN architecture. From the results, it can be seen that the MRAC based model is capable of auto-learning and has excellent control and speed tracking performance and ability to reduce the effect of parameter variations compared to conventional PID controllers. 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.

## REFERENCES

- [1]. Astrom, K.J. and Wittenmark, B. (2000). *Adaptive Control*, 2nd ed., Englewood Cliff, NJ: Prentice Hall, pp.187-222.
- [2]. J.R.Hendershot and T.J.E.Miller, “Design of brushless Permanent – magnet Motors”; Oxford, UK: Oxford Science, 1994.
- [3]. P.Pillay and R.Krishnan, “Modeling, Simulation and Analysis of Permanent-magnet Motor Drives, part II: The brushless DC Motor Drive,” *IEEE Transactions on Industry applications*, vol.25,no.2,march/April 1989.
- [4]. A.K.Wallace and R.Spee, “The effects of motor parameters on the performance of brushless DC drive,” *IEEE Transactions on Power Electronics*, vol.5, no.1, pp.2-8, January 1990.
- [5]. Varatharaju, V. M., Mathur.B.L., Udhyakumar.K., “Speed control of PMSBLDC motor using MATLAB/Simulink and effects of load and inertia changes,” 2010 2nd International Conference on Mechanical and Electrical Technology(ICMET) 10-12 Sept.2010, pp.543-548.