Indian Journal of Science and Technology, Vol 9(14), DOI: 10.17485/ijst/2016/v9i14/88728, April 2016
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Enhancement of Variable Speed Brushless DC Motor using Neural Network

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Abstract

Background/Objectives: Direct Current (DC) motor plays an important role, especially in the industry as it is used in various applications as consequences from its unique characteristic. However, some limitations of variable speed DC motor cause the application of DC motor become less effective whereas some available speed controllers have difficulties in controlling the motor speed. An improved design based on neural network controller for the Brushless Direct Current (BLDC) permanent magnet motor drives is introduced in this paper. The variable input speed is applied to the controller in order to maintain the BLDC motor output speed. **Methods/Statistical Analysis:** In the proposed enhanced scheme, the mathematical model of BLDC motor and a back propagation Artificial Neural Network (ANN) algorithm are considered and included to replace the conventional method of Proportional Integral Derivative (PID). The proposed ANN algorithm is based on the plant information, where the number of input and output neurons in each layer of the network are designed to be equivalent to the input and output number of signals of the proposed system. The architecture of the proposed ANN controller is designed to has a 2-3-1 structure of the network, where the two input neurons will exist in the input layer. For the first incoming neuron is the different signal among the desired and the real signal. Meanwhile, the second input neuron illustrates the differ between earlier error signal and the ongoing error signal. The network parameter is updated once the process for learning model is defined to ensure the ANN is appropriate to be applied in the proposed system and meet the motor features. **Findings:** From the analysis, the output error of the system effectively decreases once the training method is implemented where sufficient training dataset for the input-output mapping plant is significantly acquired. The analysis of overshoot, rise time and steady state error for the speed range between 1000 and 1500 rpm indicates that the proposed Neural Network Control (NNC) technique has successfully improved the performance of the BLDC motor drive and outperforms the conventional state-of-the-art methods. **Applications/Improvements:** The complete simulation model of BLDC motor using NNC controller has been developed. In order to make it more effective, the implementation of the simulation work into the real hardware to investigate the performance of BLDC motor become more interesting. Besides, the NNC controller can be implemented in other applications such as DC-DC converter, permanent magnet synchronous motor or servo motor.

Keywords: BLDC Motor Drives, MATLAB/Simulink, Neural Network, Neural Network Controller, PID Controller

1. Introduction

Nowadays, the application of Brushless Direct Current (BLDC) motor is commonly applied in variety industries. By recognizing some upgrading in term of compact body, good achievement, modest architecture, great accuracy and huge output torques, Brushless DC motors become more popular. However, for some reasons such as historical, technical and economic incentives, the conventional Direct Current (DC) motor machines still have been the implored choice for most automotive applications[1]. An ordinary DC motors have a lot of pleasant characteristics such as good effectiveness, smooth speed control and linear torque speed features. Besides, the DC

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motor is able to run in simple control process and does not require complex hardware[2].

DC motor has some disadvantages related to the limited lifetime of brushes. Limited reliability that caused by the wear down brush due to the operation and the need of replacement is one of the disadvantages of DC motor. Consequences, BLDC motor have been used to overcome such problem. BLDC motor is free from any extra DC supply compared to an ordinary DC motor since the supply from flux is regarding to the stable magnet. A lower reliability occurs because of the wear down brush and the need of maintenance or replacement[3]. As for the solution, BLDC motor has been replaced to solve the aforementioned problems. The Brushless DC motor has major benefits over the conventional separately excited DC motor, where its free from any extra DC supply compare with an ordinary DC motor since the supply from flux is regarding to the stable magnet[4]. BLDC motor is also designed with compressed body, long operating life and higher speed range. It is robust and has high efficiency[5]. BLDC motors also offer additional advantages such as high torque to inertia ratios, greater speed capabilities and better operational speed versus torque characteristics.

Many machine designs and the performance of BLDC motor drives can be improved by a few methods such as the machine design and control scheme of motor itself[6]. Besides, the well known of motor model results in advantageous of implementation ineffective motor control in the simulation[7]. Some approaches of motor control have been recommended in order to expand the BLDC motor performance[8]. Several simulation modelings which are based on fuzzy logic control, Neural Network Control and neural network Proportional Integral Derivative (PID) control have been discussed[9–12]. The BLDC motor with an excellent simulation model by applying the fuzzy logic controller has been developed[13]. On the other hand, some implementations of the same method have been discussed regarding the fuzzy logic control for BLDC motor.

Nevertheless, the conventional PID controlled DC motor drives have difficulty to elaborate the mathematical models in order to describe the system dynamic. Consequence of the problem in identifying the mathematical model of PID controller, the system fails to obtain the accurate control of the motor. A BLDC motor is classed as a nonlinear model that have some parameters such as saturation disturbances and parameter drifts that could not be avoided and hardly to be modeled accurately. The nonlinear mechanical characteristics differ with the motor models and these differences cause the drive system unstable and highly dependent on the parameter value.

Therefore, Artificial Neural Network (ANN) controllers have been implemented to analyze BLDC motor drives. In this system, an adaptive controller is responding by neural network has the capability to recognize the structure and parameter of the controlled object. The controlled object by Neural Network Control (NNC) offer the necessary mechanism law without the accurate model. Hence, it will give better regulating ability and strength related to PID control technique.

The nonlinear control system can be illuminated through the Back Propagation (BP) neural network. Therefore, the problem faces on an ordinary PID controller can be solved in term of obstacle to define the criteria on-line stage and the nonlinear time varying structure can be control successfully. The current neural system control has a high value of real-world presentation.

The simulation model of BLDC motor drive with included NNC as a controller has been derived in this paper by using MATLAB/Simulink. The NNC controller produced has the capability to acquire immediately and familiar with the controller parameters which depend on the internal disruption and internal difference of the converter including minimizing the steady state error, overshoot and rise time of the output voltage.

2. Methodology

2.1 The Permanent Magnet BLDC Motor Arrangement

The BLDC motor circuit diagram that consists of three phase Voltage Source Inverter (VSI) scheme is connected with Brushless DC motor is shown in Figure 1. The fixed stator winding and the rotor are included in the BLDC

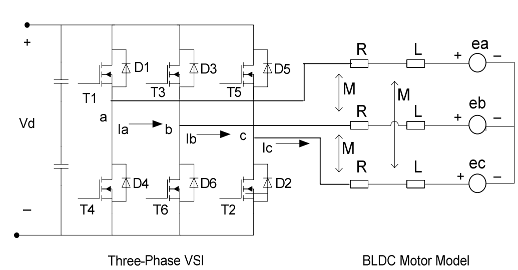

Figure 1. Brushless DC motor simulation block diagram.

motor. Basically, three phase stator winding with three separate voltages are applied to the windings.

2.2 BLDC Motor Drive Modelling and Simulation System

By referring Figure 2, the simulation block diagram for BLDC motor is illustrated. Based on the proposed system, the study of BLDC motor is concentrated on the assumption for interpretation and precision. The BLDC motor is considered as an unsaturated type. All the winding for stator resistances are equivalent, meanwhile the self and mutual inductance are constant. The inverter in semiconductor devices is ideal and iron losses are ignored.

The waveform for back Electromagnetic Field (EMF) are equal in all phases. By referring the corresponding circuit of BLDC motor and the VSI arrangement exposed in Figure 1, the equations for dynamic BLDC motor by using the assumption can be imitative as[14]:

$$V_a = RI_a + (L-M)\frac{di_a}{dt} + e_a \tag{1}$$

$$V_b = RI_b + (L-M)\frac{di_b}{dt} + e_b \tag{2}$$

$$V_c = RI_c + (L-M)\frac{di_c}{dt} + e_c \tag{3}$$

Where the phase voltage are assigned as V_a, V_b and V_c, the phase current are express i_a, i_b and i_c, e_a, e_b and e_c are the phase back EMF and is differential operator, self-inductance is known as L, thus the mutual inductance is notated as M and R mean phase resistance. The equation of motion can be expressed as:

$$\frac{d\omega_m}{dt} = \left(\frac{P}{2J}\right)(T_e - T_L - B\omega_r) \tag{4}$$

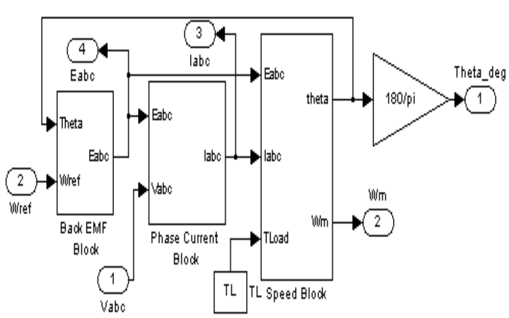

Figure 2. Brushless DC motor simulation block.

$$\frac{d\theta}{dt} = \omega_r \tag{5}$$

Where the electromagnetic torque is defined as T_e, the load torque is known as T_L in Nm, the moment of inertia in kgm^2 is called as J, B is represent the frictional coefficient in Nms/rad, rotor speed is assign as ω_m in mechanical rad/s and ω_r is rotor speed in electrical rad/s.

2.2.1 Trapezoidal Back EMF Design

The waveform of trapezoidal back EMF represents the function of rotor position. Thus, the rotor position can be calculated by referring to the operation speed[15]. The rotor position function (θ_r) that represents the back EMFs can be expressed as:

$$e_{abc} = f_{abc}(\theta_r) \tag{6}$$

$$E = k_e\,\omega_r \tag{7}$$

Where the back EMF constant is known as (k_e)and the rotor position function is notated as $f_{abc}(\theta_r)$. Figure 3 is the BLDC motor illustration block diagram for trapezoidal back EMF and phase current waveform. The back EMF is a function of rotor position (θ_r) and has the amplitude ($E = k_e\,\omega_r$). The back EMFs is able to defined the electromagnetic torque as follows[16]:

$$T_a = \frac{e_a i_a}{\omega_r} \tag{8}$$

$$T_b = \frac{e_b i_b}{\omega_r} \tag{9}$$

$$T_c = \frac{e_c i_c}{\omega_r} \tag{10}$$

The back EMF can be generated from the rotor position by neglect the damping factor that express the speed and BLDC torque characteristics which derived as:

$$\omega_m = \frac{P}{2J}\int (T_e - T_L)\,dt \tag{11}$$

The block diagram of speed and torque control circuit is shown in Figure 4.

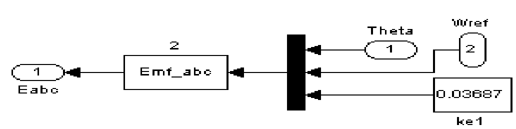

Figure 3. Block diagram simulation for back EMF generates from rotor position.

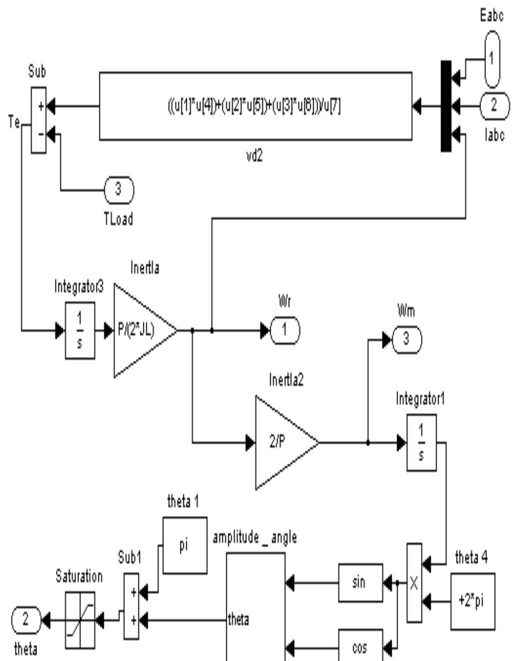

Figure 4. The speed and electromagnetic torque of BLDC motor simulation block.

2.2.2 *Voltage Source Inverter*

Regarding to the Figure 1, the conduction of operating modes is only excited through the two phases. Hence, three phase current will be used to represent the line-to-line voltages. Voltage of three phase system can be derived as Equations (12) to (14) respectively.

$$V_{ab} = 2Ri_1 + 2(L-M)\frac{di_1}{dt} + e_{ab} \tag{12}$$

$$V_{bc} = 2Ri_2 + 2(L-M)\frac{di_2}{dt} + e_{bc} \tag{13}$$

$$V_{ca} = 2Ri_3 + 2(L-M)\frac{di_3}{dt} + e_{ca} \tag{14}$$

Where i_1, i_2 and i_3 are the loop currents, meanwhile the line-to-line back EMFs are declared as e_{ab}, e_{bc} and e_{ca}. The line-to-line back EMFs can be obtained as:

$$e_{ab} = e_a - e_b \tag{15}$$

$$e_{bc} = e_b - e_c \tag{16}$$

$$e_{ca} = e_c - e_a \tag{17}$$

Meanwhile, the phase current can be expressed as:

$$i_a = i_1 - i_3 \tag{18}$$

$$i_b = i_2 - i_1 \tag{19}$$

$$i_c = i_3 - i_2 \tag{20}$$

By referring the hysteresis block, the switching function, V_abc is obtained. The midpoint of the DC supply voltage, V_{dc} that can be considered as:

$$V_{ao} = \frac{V_d}{2} V_a = \frac{V_d}{2} \sum_{0}^{\infty} A_n \sin(n\omega t) \tag{21}$$

$$V_{bo} = \frac{V_d}{2} V_b = \frac{V_d}{2} \sum_{0}^{\infty} A_n \sin\left[n(\omega t - 120)\right] \tag{22}$$

$$V_{co} = \frac{V_d}{2} V_c = \frac{V_d}{2} \sum_{0}^{\infty} A_n \sin\left[n(\omega t - 240)\right] \tag{23}$$

Next, the equation for the inverter line-to-line voltage can be expressed:

$$V_{ab} = V_{ao} - V_{bo} \tag{24}$$

$$V_{bc} = V_{bo} - V_{co} \tag{25}$$

$$V_{ca} = V_{co} - V_{ao} \tag{26}$$

The simulation blocks of the aforementioned numerical PWM inverter are shown in Figures 5 and 6 respectively.

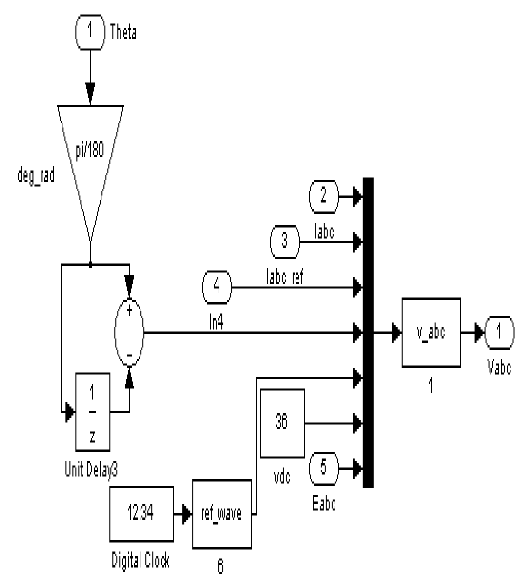

Figure 5. The simulation block for line-to-line voltage inverter.

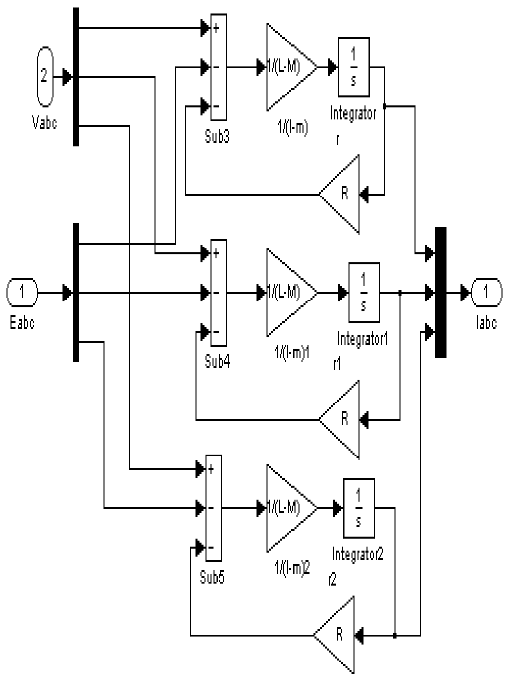

Figure 6. Simulink diagram of three phase currents.

2.3 Neural Arrangement and Learning Algorithm

2.3.1 Configuration of Neural Network Controller

The mechanism of neural network is constructed regarding to the plant information. Generally, the input and output number of neurons in every level are equivalent to the input and output number of signals of the structure separately. Figure 7 shows the configuration of the proposed NNC of a BLDC motor[17].

The proposed NNC has a 2-3-1 structure design of the network. Two input neurons exist in the input layer where the initial input neuron represents the error signal among desired signal and actual signal. Meanwhile, the next input neuron refers to the changes on previous error signal and current error signal.

The w_{ij} is the link of weight parameter among j_{th} and i_{th} neuron at m_{th} layer, whereas b_{mi} is the bias parameter of this layer at i_{th} neuron. The transfer function of the system at t_{th} neuron in m_{th} layer which is interpreted as:

$$n_i^m = \sum_{j=1}^{S^{m-1}} w_{ij}^m a_j^{m-1} + b_i^m \tag{27}$$

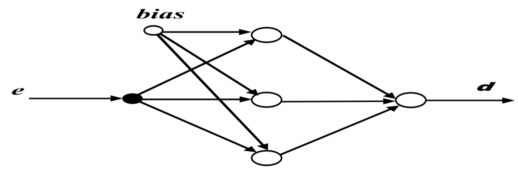

Figure 7. The proposed neural network controller structure.

The output function of neuron in m^th^ layer is given by:

$$a_i^m = f^m(n_i^m) \tag{28}$$

Where the neuron activation function is known as *f*. In order to ensure the output layer and the hidden layer becomes harmony and a tangent hyperbolic function respectively, the activation function is designed smoothly.

The mechanism of neural network is constructed based on the plant information. Input and output number of neurons in each level are equivalent to the input and output number signals of the system respectively. The activation function of the hidden layer is given as:

$$f^m(n_i^m) = \frac{2}{1+e^{-2n_i^m}} - 1 \tag{29}$$

An updating for connection weight and bias parameter can be determined as:

$$w_{ij}^m(k+1) = w_{ij}^m(k) + \alpha \frac{\partial F(k)}{\partial w_{ij}^m} \tag{30}$$

$$b_i^m(k+1) = b_i^m(k) + \alpha \frac{\partial F(k)}{\partial b_i^m} \tag{31}$$

Based on the expression above, the sampling time is called k, the learning rate known as α and F is significant for the performance index function of the network.

2.3.2 Voltage Source Inverter

2.3.3.1 Neural Network Learning Algorithm

After modeling the neural network architecture, the update process for network parameter is produced by the learning model. This step ensures that ANN is suitable to be applied in the proposed system and matches with the motor characteristics[18]. The applied training process could minimize the output error of the network in which a sufficient training dataset for the input-output mapping plant is sufficiently acquired[19].

On the other hand, the back propagation algorithm is also developed as temperature and magnetic saturation can be varied as motor parameter. The first order optimization scheme will be enclosed for updating network parameters. The index sum of the square error effectiveness is assumed by[20]:

$$F(k) = \frac{1}{2}\sum_{i} e_i^2(k) \quad (32)$$

$$e_i(k) = t_i(k) - a_i(k) \quad (33)$$

Where t_i is target signal and a_i is an output signal on last layer. The gradient descent of the performance index against to the connection weight is given by:

$$\frac{\partial F}{\partial w_{ij}^m} = \frac{\partial F}{\partial n_i^m}\frac{\partial n_i^m}{\partial w_{ij}^m} \quad (34)$$

The network sensitivity factor can be derived as:

$$s_i^m = \frac{\partial F}{\partial n_i^m} \quad (35)$$

$$s_i^m = \frac{\partial F}{\partial a_i^m}\frac{\partial a_i^m}{\partial n_i^m} \quad (36)$$

The connection weight parameter reflect to the gradient transfer function is given by:

$$\frac{\partial n_i^m}{\partial w_{ij}^m} = a_i^{m-1} \quad (37)$$

From substitution of Equations (35) and (37) into (30), the parameter for restoring connection is assumed as:

$$w_{ij}^{m-1}(k+1) = w_i^{m-i}(k) + \alpha s_i^m(k) a_i^{m-1}(k) \quad (38)$$

With the same technique, the updating bias parameter is given by:

$$b_i^{m-1}(k+1) = b_i^{m-i}(k) + \alpha s_i^m(k) \quad (39)$$

3. Results and Discussion

According to the proposed controller, the simulation block diagram of BLDC motor has been carried out to analyze the performance of the controller by using Simulink-MATLAB. Figure 8 represented the proposed block diagram for BLDC motor using NNC controller. Table 1 displays the Brushless DC motor specification during the simulation activities.

The differences between the traditional PID controller and the schemed NNC will be analyzed in this simulation.

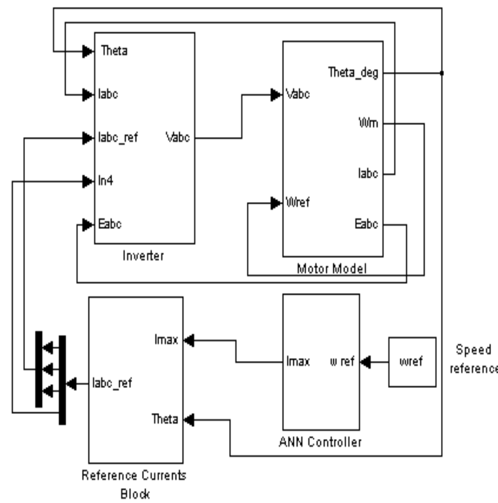

Figure 8. The schemed simulation block for BLDC motor using NNC control.

Table 1. Parameters of BLDC motor

Symbol	Parameter	Value
R_s	Phase resistance	4.31 (ohm)
L	Phase inductance	35.604 (mH)
K_e	Back EMF constant	3.86 (V/1000 rpm)
K_t	Torque constant	36.8 (mNm/A)
P	Pole pairs	1
J_m	Rotor inertia	11 x 10^{-6} (kgm^2)
T	Peak torque	154 (mNm)
Vdc	Rated voltage	36 (volt)

The proposed NNC is designed for acceptable variable speed of input to control BLDC motor. These simulations focus for speed range between 1000 rpm to 1500 rpm only. By referring the simulation result achieved, it can be stated that the output speed will remain same as the input reference applied.

Simulation result of the three phases symmetric back EMF is presented in Figure 9. Figure 10 represents the three phase current waveforms. The phase current is obtained based on the line to line voltage and back EMF voltage. The back EMF and phase current obtained which based on the speed during 1500 rpm.

The illustration of Figure 11 is the phase current reference waveform for BLDC motor. The phase current

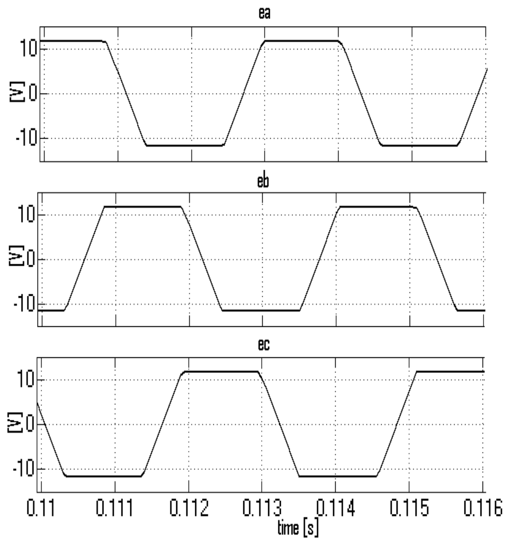

Figure 9. The waveform for back EMF during the rotor position at speed 1500 rpm.

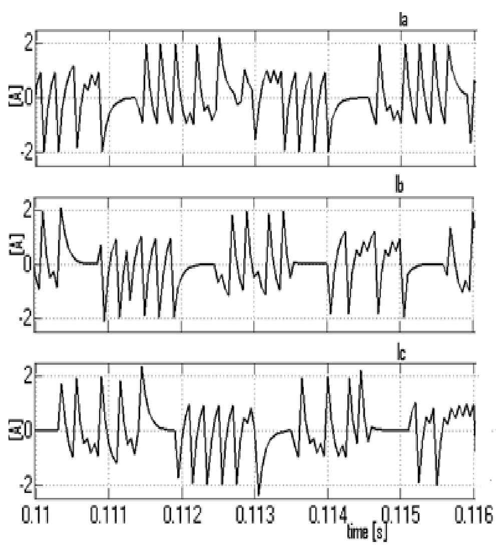

Figure 10. Waveform for phase current during the rotor position at speed 1500 rpm.

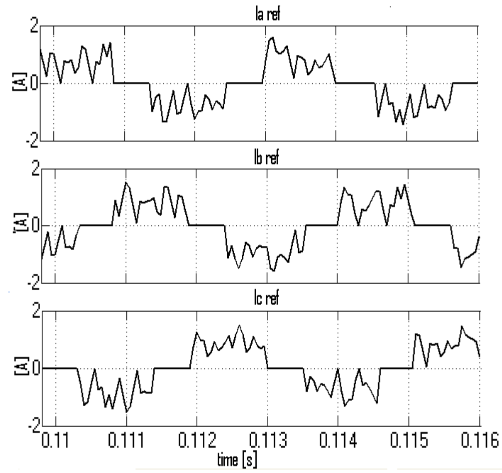

Figure 11. The waveform through speed 1500 rpm for phase current reference.

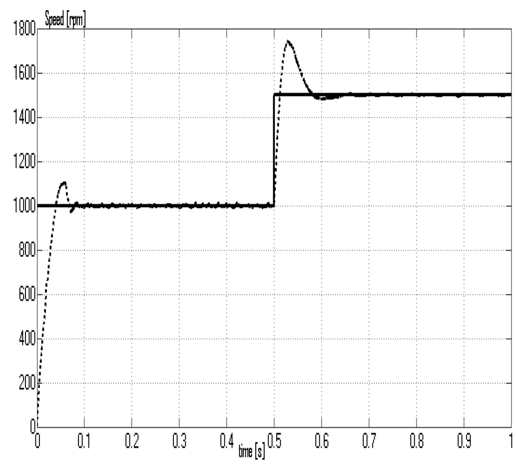

Figure 12. Waveform for speed performance during step up speed reference of PID controller.

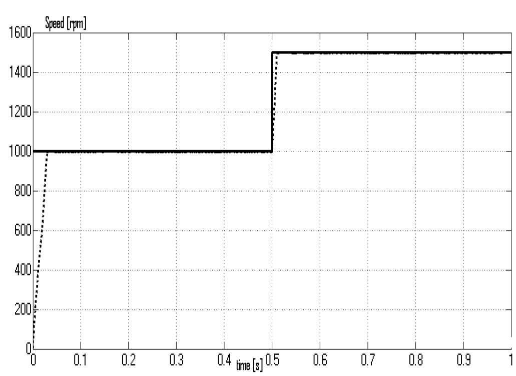

Figure 13. Waveform for speed performance during step up speed reference of NNC controller.

reference is generated based on the rotor position, (θ_r) and reference current amplitude (I_{max}). The reference current amplitude (I_{max}) created when the control signal reached from Neural Network Controller is divided by the torque constant of BLDC motor.

The simulation result for step up tracking speed implemented towards BLCD motor display in Figure 12 and Figure 13. The tuned for PID produces 10.3% overshoot with 0.04s rise time and steady state error during 0.09s before achieved the reference speed. Figure 13 shows the step up tracking performance of the NNC controller. Based on the result obtained, it found the overshoot is reduced to 0.15% with rise time reduces as well as 0.03s before the system stable. The results show that during starting up, the speed performance of scheme NNC yields better improvement compared to PID controller such as eliminating overshoot and reduce the rise time to achieve desired output speed.

Figure 14 and Figure 15 represent the step down tracking speed of PID controller and NNC controller. The tuned for PID produces 16.5% overshoot with 0.043s rise time and steady state error during 0.32s before achieved the reference speed. Based on the result obtained from NNC controller, it found the overshoot is reduced to 0.1% with rise time reduces as well as 0.0405s before the system stable. The results show that during starting down the speed of the schemed NNC yield better improvement compared to PID controller such as eliminating overshoot and reduce the rise time to achieve desired output speed.

Another experiment is the controller will evaluate for the effect of nominal load disturbances. The waveform for the speed tracking response via the PID controller is viewed in Figure 16, meanwhile Figure 17 represents the speed tracking response for NNC controller. It is obviously indicated that the NNC controller created significant steady state error since no integral mechanism occur, but the PID controller has an overshoot and more settling time.

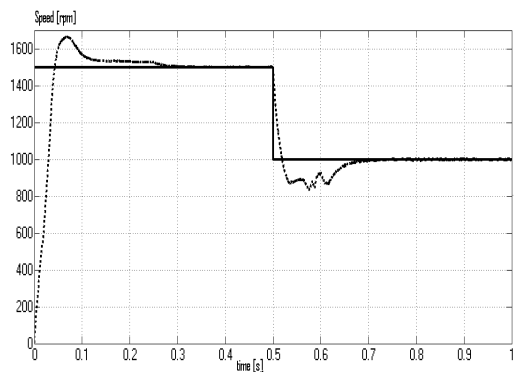

Figure 14. Waveform for speed performance during step down speed reference of PID controller.

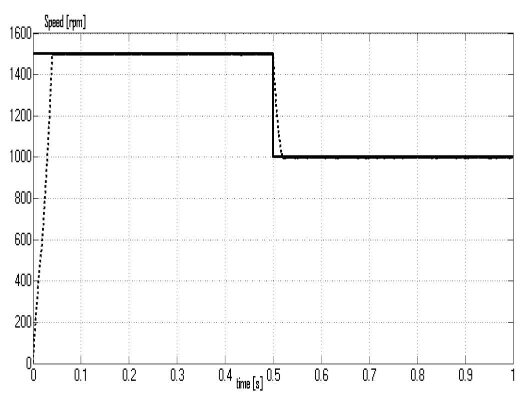

Figure 15. Waveform for speed performance during step up speed reference of NNC controller.

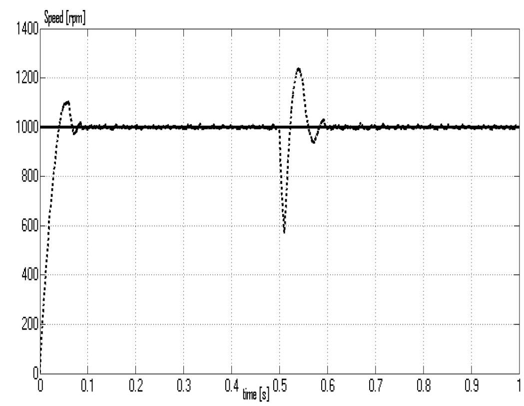

Figure 16. Waveform for speed performance throughout step load disturbance of PID controller.

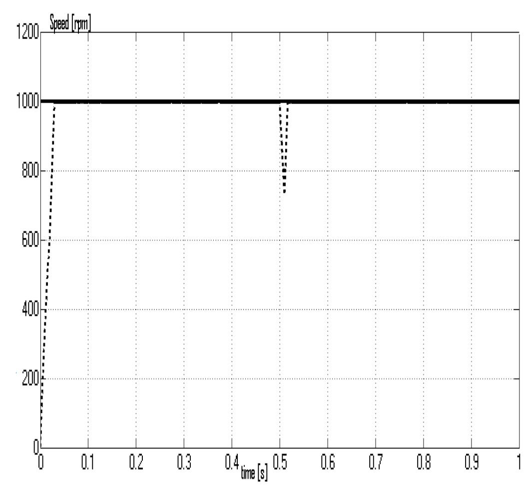

Figure 17. Waveform for speed performance throughout step load disturbance of NNC controller.

4. Conclusion

This research introduces the Neural Network Controller to control the BLDC motor drive. The enforcement of the Neural Network Controller can be enhanced by a learning algorithm based on the back propagation scheme. Two simulation tests have been carried out to investigate the effect on the BLDC motor efficiency. By applying the NNC towards the BLDC motor, the outcome simulation display that it capable to reach better performance compared to the PID controller in term of overshoot, steady state error and rise time. The NNC reduces obviously to improve the dynamic response such as reduce the overshoot and rise time.

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