SIMULATION OF A VARIABLE SPEED BRUSHLESS DC MOTOR USING NEURAL NETWORK CONTROLLER

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This paper presents a control scheme of a neural network for the brushless direct current (BLDC) permanent magnet motor drives. The mathematical model of BLDC motor and artificial neural network algorithm is derived. The controller is designed to tracks variations of speed references and stabilizes the output speed during load variations. The BLDC has some advantages compare to the others type of motors, however the nonlinearity of the BLDC motor drive characteristics, cause it is difficult to handle by using conventional proportional-integral-differential (PID) controller. In order to overcome this main problem, a neural network controller with online learning technique based on back propagation algorithm is developed. The effectiveness of the proposed method is verified by develop simulation model in MATLAB-Simulink program. The simulation results show that the proposed neural network controller (NNC) produce significant improvement control performance compare to the PID controller for both condition controlling speed reference variations and load disturbance variations.
CHAPTER 1

INTRODUCTION

1.1 Project Background

Brushes DC motors have many attractive properties such as smooth speed control and linear torque-speed characteristics. Besides that, the control of DC motor also simple and does not require complex hardware.

However, DC motors have main disadvantage regarding to the limited lifetime of brushes. A lower reliability occurs caused by the brushed wear down by operation and need-time to time maintenance or replacement (Hong, W. et al., 2007).

BLDC motors offer some advantages such as simple structure and compact in size, reliable performance, robust and highly efficient. BLDC motors also offer additional advantages such as greater speed capabilities and better speed versus torque characteristics. Due to the BLDC operate without brushes it life spent can be increased and maintenance operation also can be avoided.

Nowadays, the application BLDC motors are widely used in many industries as growth as the rapidly developments in power electronic technology, manufacturing technology for high performance magnetic materials and modern control theory for motor drives.

Classical PID controllers are commonly used in industries due to their simplicity and ease of implementation (Rubai, A. et al., 2008). In linear system model, controller parameters of the PID controller are easy to determine and resulting good control performances. However, for nonlinear system model applications such as BLDC motor drive, control performance of the PID controller
becomes poor and difficult to determine the controller parameters (Hong, W. et al., 2007 and Tipsuwanporn, V. et al., 2002).

In order to improve control performance of the BLDC motor drive, several intelligence controllers such as fuzzy logic control, neural network control and hybrid neuro-fuzzy control methods for BLDC motor have been reported in (Rubaai, A. et al., 2008, Tipsuwanporn, V. et al., 2002, Mahdavi, J. et al., 2011, Lee, B. K. et al., 2003, Cunkas, M. et al., 2010, Gokbulut, M. et al., 2007, Ji, H. et al., 2008 and Ji, H. et al., 1997).

Developments of the fuzzy logic controls for BLDC motor drive have been reported in (Tipsuwanporn, V. et al., 2002, Mahdavi, J. et al., 2011, Lee, B. K. et al., 2003, Cunkas, M. et al., 2010) respectively. Implementations of the neural network control (NNC) for BLDC motor drive have been proposed in (Ji, H. et al., 2008, Ji, H. et al., 1997, Utomo, W. et al., 2011 and Senju, T. et al., 1997).

In addition, the NNC also have been applied for several others power electronic and motor drive applications (El-Balluq, T. NN. et al., 2004 and Shanmugasundram, R. et al., 2009). In order to improve performance of the NNC some researchers have been done to develop online learning scheme of the NNC.

In this project, a complete simulation model with neural network control (NNC) method for BLDC motor drive is proposed using Matlab/Simulink. The develop NNC has the ability to learn instantaneously and adapt its own controller parameters based on external disturbance and internal variation of the converter with minimum steady state error, overshoot and rise time of the output voltage.

The structure of this paper is as follows: Chapter II discusses the system structure of BLDC motor and the development of dynamic modeling for BLDC motor such as phase currents, voltage, rotor speed and mechanical torque. In Chapter III, an introduction to concept and design of online learning neural network control is described. The simulation results are analyzed in Chapter IV. Finally, the conclusions are summarized in Chapter V.
1.2 Problem Statement

There are mainly two types of dc motor used in the industry. The first one is conventional brushes dc motor and the second type is brushless dc motor (BLDC). For the speed control applications, the DC motor was chosen due to the control simplicity on the intrinsic decoupling between the flux and the torque. However, there are physical limitations to speed and life time because of brush wear. This DC motor's weakness can be eliminated by using a BLDC motor. Since there are no carbon brushes to wear out, a BLDC motor can provide significantly greater life being now only limited by bearing wear.

PID controllers have the advantages in term of simple structure and low cost controller. However, when applied the non-linear system, the PID controller not capable to approach the best performance. Neural network controllers are well suited to control system with the capabilities to approach any nonlinear system controlled object. Since the BLDC motor is a non-linear system thus, the back propagation neural network controller will be developing to improve the performance of variable speed of BLDC motor.

1.3 Project Objectives

The objectives of this project are:

(i) To derive develop simulation model of a brushless direct current (BLDC) motor by using Matlab Simulation
(ii) To develop variable speed neural network controller to the BLDC motor
(iii) To improve speed performances of the BLDC motor such as reduces overshoot; reduce rise time and steady state error.
1.4 Project Scopes

The scopes of this project are to simulate the BLDC motor using MATLAB simulink software and develop the neural network controller that will be used to control the variable speed of the BLDC motor. The structure of the NNC will be used in this project consist of three layer with two neuron at input layer and single output layer. The PID controller and variable speed BLDC motor drive also will be develop to compare the effectiveness of the proposed controller.
CHAPTER 2

LITERATURE REVIEW

2.1 Technology Developments

Many approaches for designing controller based on the brushless DC motor has been proposed on the previous papers. By referring to the (Cunkas, M. et al., 2010), the research focused on an efficient simulation model of brushless direct current (BLDC) motor by applying the fuzzy logic as the controller. Basically the simulation model developed many dynamic characteristic such as phase currents, voltages, rotor speed and mechanical torque. Meanwhile the fuzzy logic controller is designed purposely to ensure the real speed and torque value is able to reach in a short time. The result obtained from fuzzy logic controller will compared with the PID controller. The result shows that the fuzzy logic controller is better performance compared with PID controller. Another simulation of BLDC motor reported in (Lee, B. K. et al., 2003). The dynamic characteristic of speed and torque as well as voltage and currents of pwm inverter component have been developed and analyzed. The expectation from the modeling block simulation proved with the reduction computation time and memory size achieved.

Development of Proportional-Derivative and Integral (PD-I) type Fuzzy-Neural Network Controller (FNNC) based on Sugeno fuzzy model is proposed for brushless DC motor drives to achieve satisfied performance under steady state and transients conditions presented in (Gokbulut, M. et al., 2007). The PD-FNNC is activated during transient states and the PI-FNNC is activates in steady state region. The experiment result focused on the performance of various control approaches on different type of controller. Based on the result obtained, it shows that the PD type
FNNC produces significant steady state error compared to other. Development of a fuzzy logic controller using MATLAB Fuzzy-Logic Toolbox for brushless direct current (BLDC) permanent magnet motor drives also presented in (Siong, T. C. et al., 2011). In order to identify the performance of the controller, the simulation results are compared with TMS320F2808 experimental results. The results show both simulation and experimental are matched as expected. Development of BLDC motor speed control using PID based on the BP neural network self-tuning PID parameter discussed in (Ji, H. et al., 1997). The traditional PID controller is applied initially for a few seconds followed by another parameter self-tuning PID controller based on BP neural network is exchanged to the controller parameter. By using parameter self-tuning PID controller based on BP neural network, it solved the difficulties of the traditional PID controller to determine the parameters on line moment and effectively control nonlinear time varying system.

Another concept applied in (Senjyu, T. et al., 1997) research which applied vector control using neural network as an efficient method to control the variable speed control of brushless DC motor. Compared with the conventional vector controller that experience with electrical machine parameter variations because these controllers depend on the parameters, the vector control using neural network is proposed as on-line estimator of the nonlinear dynamic equations of brushless dc motor. The vector control using neural network capable to maintain control performance without electrical machine parameter variations by assume the nonlinear dynamic equation of brushless DC motor on-line.

In (Li, Z., 2009) presented about combination control between cerebellar-model-articulation computer (CMAC) neural network and PID controller for the brushless DC motor. This paper used the CMAC neural network as the main control and the mathematical model of square-wave PM brushless DC motor is produced and applied to the simulation block models. Based on the simulation, there are different situation results for the conventional PID controller and the combine controller was produced. The result focused during the system under the simultaneously changes of torque and velocity signals. From the results, it shown that when combining algorithm is presented, the overshoot has been greatly decreased and the motor can reach its steady state more quickly. In the case of velocity changed, the CMAC NN and PID combining control can shorten the settling time compared with ordinary PID control with a better tracking performance.
2.2 Brushless Direct Current Motor (BLDC)

Brushless Direct Current (BLDC) motors are one of the famous motor types recently. BLDC motors are used in industries such as Appliances, Automotive, Aerospace, Consumer, Medical, Industrial Automation Equipment and Instrumentation. There is variety of design BLDC motor for various applications. Some BLDC motors are designed to rotate at the constant speed especially for those used in the disk drives and some are designed to control the speed by varying the applied voltage to motors. In the other hands, another application of BLDC motors have build in tachometer that will give the output pulses as the motor rotates. The type of this application normally applied to both disk drive motors and some computer fans. Generally, BLDC motors do not use brushes for commutation but applied electronically commutated. BLDC motors have many advantages over brushed DC motors and induction motors such as better speed versus torque characteristics, high dynamic response, high efficiency and higher speed ranges.

2.2.1 Construction and Operating Principle

BLDC motors are a type of synchronous motor. This means the magnetic field generated by the stator and rotor rotate at the same frequency. BLDC motor does not operate directly off a DC voltage source. It consists of a rotor with permanent magnets, a stator with windings and commutation that is performed electronically. Normally three Hall sensors are used to detect the rotor position and commutation is performed based on Hall sensor inputs. There are two types of stator windings variants which are trapezoidal and sinusoidal motors.

2.2.1.1 Stator

The stator of a BLDC motor consists of stacked steel laminations with windings placed in the slots that are axially cut along the inner periphery as in Figure 2.1. Most BLDC motors have three stator windings connected in star connection. The winding formed when each of these winding are constructed with numerous coils
interconnected together. The stator windings construct into two types which is trapezoidal and sinusoidal motors.

![Stator of BLDC Motor](image)

Figure 2.1: The stator of BLDC motor

2.2.1.2 Rotor

The permanent magnet is used to form the rotor and be able to vary from two to eight pole pairs with alternate North (N) and South (S) pole. The proper magnetic material is chosen to produce the rotor regarding to the required field density in the rotor. Figure 2.2 shows cross sections of different arrangements of magnets in a rotor.
2.2.1.3 Hall Sensor

The BLDC motor has a commutation that controlled electronically. The stator winding must be energized in a sequence mode in order to rotate the BLDC motor. The rotor position must be well recognized in order to know which winding will be energized following the energizing sequence. A Hall Effect sensor is embedded into the stator and sensed the rotor position. Most BLDC motor consists of three Hall effect sensors and the combination of this sensors will produce the exact sequence of commutation. Figure 2.3 represents a cross section of a BLDC motor with rotor that has alternate North (N) and South (S) permanent magnets. There are two output versions by referring the physical position of the Hall sensors either at 60° or 120° phase shift to each other.
2.2.1.4 Theory of Operation

Three windings on each commutation have different function. First windings will energized to positive power (current inflow into the winding), the second winding for negative (current out flow the winding) and the last winding is in a non-energized condition. The interaction between the permanent magnet and magnetic field generated by the stator coils will produce the torque. Basically, the peak torque occurs when these two fields are at 90° to each other and falls off as the field move together. In order to keep the motor running, the magnetic field produced by the winding should shift position as the rotor moves to catch up with the stator field.

2.2.2 Torque/Speed Characteristics

An example of torque/speed characteristic is shows in the Figure 2.4. Based on the figure below, the BLDC motor can define using two torque parameters, a peak torque (TP) and rated torque (TR). The motor can be loaded up to the rated torque during continuous operations. As mention earlier, the torque remains constant in a BLDC motor for speed range up to the rated speed. Meanwhile it capable to run up to the maximum speed which is 150% of the rated speed but the torque starts dropping during this situation.

![Figure 2.4: Torque/Speed Characteristic](image)

Figure 2.4: Torque/Speed Characteristic
2.2.3 Commutation Sequence

Figure 2.5 shows the Hall sensors signals with respect to back EMF and the phase current. Every 60 electrical degrees of rotation, one of the Hall sensors changes the state. Given this, it takes six steps to complete an electrical cycle. In synchronous, with every 60 electrical degrees, the phase current switching should be updated. However, one electrical cycle may not correspond to a complete mechanical revolution of the rotor. The number of electrical cycles to be repeated to complete a mechanical rotation is determined by the rotor pole pairs. For each rotor pole pairs, one electrical cycle is completed. So, the number of electrical cycles/rotations equals the rotor pole pairs.

Figure 2.5: The hall sensor output and trapezoidal back EMF waveforms of BLDC motor drive
2.2.4 Back EMF

The back Electromotive Force (EMF) occurs when the winding generates a voltage during rotating the BLDC motor. The energized voltage is in different direction to the polarity of back EMF. There are three factors that caused back EMF which are angular velocity of the rotor, magnetic field generated by rotor magnets and the number of turns in the stator windings. The rotor magnetic field and the number of turns in the stator winding remain constant when the motor is designed. The factor influenced control back EMF is the angular velocity or speed of the rotor. The back EMF will increase as well as the speed increases.

The potential difference across a winding can be calculated by subtracting the back EMF value from the supply voltage. The motors are designed with a back EMF constant in such a way that when the motor is running at the rated speed, the potential difference between the back EMF and the supply voltage will be sufficient for the motor to draw the rated current and deliver the rated torque. If the motor is driven beyond the rated speed, back EMF may increase substantially, thus decreasing the potential difference across the winding, reducing the current drawn which results in a drooping torque curve. The last point on the speed curve would be when the supply voltage is equal to the sum of the back EMF and the losses in the motor, where the current and torque are equal to zero.

2.3 Artificial Neural Network (ANN)

Figure 2.6 illustrates a Multilayer Perceptron Neural Network Model. This network consists of an input layer (on the left) with three neurons, one hidden layer (in the middle) with three neurons and an output layer (on the right) with three neurons. Each layer has some neurons that are connected to the next layer through the link.

The input layer of the neural network serves as an interface that takes information from the outside world and transmits it to the internal processing units of the network. Similarly, the output layer sends information from the neural network’s internal units to the external world. The nodes in hidden layers are the neural network’s processing units.
Figure 2.6: A perceptron network with three layers

Input Layer is a vector of variable values (x1...xp) that represented to the input. The input layer (or processing before the input layer) standardizes these values so that the range of each variable is -1 to 1. The input layer distributes the values to each of the neurons in the hidden layer. In addition to the predictor variables, there is a constant input of 1.0, called the bias that is fed to each of the hidden layers. The bias is multiplied by a weight and added to the sum going into the neuron. During hidden layer, the value from each input neuron is multiplied by a weight (wji), and the resulting weighted values are added together producing a combined value uj. The weighted sum (uj) is fed into a transfer function, σ, which outputs a value hj. The outputs from the hidden layer are distributed to the output layer.

Output Layer occurred when the value from each hidden layer neuron is multiplied by a weight (wkj), and lastly the weighted values are added together producing a combined value vj. The weighted sum (vj) is converted into a transfer function, σ, which outputs a value yk. The y values are the outputs of the network.
CHAPTER 3

METHODOLOGY

3.1 Introduction

The proposed general block diagram for variable speed BLDC motor using neural network controller is shown in Figure 3.1.

![Block Diagram](image)

Figure 3.1: The block diagram of a variable speed neural network BLDC motor drive system

3.2 System Structure

3.2.1 Structure of Permanent Magnet BLDC Motor Structure

Figure 3.2 show the circuit diagram for BLDC motor that consists of three phase voltage source inverter system and BLDC motor. The BLDC motor has the fixed stator winding and the rotor. Basically, there are three phase on the stator winding with three separate voltage are applied to the windings.
3.2.2 BLDC Motor Drive System

The analysis of BLDC motor is based on the assumption for simplification and accuracy. The BLDC motor is type of unsaturated. The stator resistances for all the winding are equal and the self and mutual inductance are constant. Semiconductor devices of inverter are ideal and iron losses are negligible. Meanwhile, the back-EMF wave-forms of all phases are equal. Based on the equivalent circuit of BLDC motor and VSI system shown in Figure 3.2, the dynamic equations of BLDC motor using the assumption can be derived as

\[ V_a = R I_a + (L - M) \frac{di_a}{dt} + e_a \]  
\[ V_b = R I_b + (L - M) \frac{di_b}{dt} + e_b \]  
\[ V_c = R I_c + (L - M) \frac{di_c}{dt} + e_c \]

(3.1)  
(3.2)  
(3.3)

Where

\[ V_a, V_b, V_c \] = Stator phase voltages  
\[ i_a, i_b, i_c \] = Stator phase currents
\[ e_{a}, e_{b}, e_{c} = \text{Phase back EMF} \]
\[ L = \text{Self inductance} \]
\[ M = \text{Mutual inductance} \]
\[ R = \text{Phase resistance} \]

The motion equation is defined as:-

\[
\frac{d\omega_m}{dt} = \left( \frac{P}{2J} \right) (T_e - T_L - B\omega_r) \tag{3.4}
\]
\[
\frac{d\theta}{dt} = \omega_r \tag{3.5}
\]

Where

\[ T_e = \text{The electromagnetic torque} \]
\[ T_L = \text{Load torque (Nm)} \]
\[ J = \text{Moment of inertia (kgm}^2 \) \]
\[ B = \text{Friction coefficient (Nms/rad)} \]
\[ \omega_m = \text{Rotor speed in mechanical (rad/s)} \]
\[ \omega_r = \text{Rotor speed in electrical (rad/s)} \]

### 3.2.2.1 A Trapezoidal Back Electromagnetic Force (EMF) of BLDC Motor

The trapezoidal back-EMF wave forms are modeled as a function of rotor position so that rotor position can be actively calculated according to the operation speed. The back EMFs are expressed as a function of rotor position (\( \theta_r \))

\[
e_{abc} = f_{abc}(\theta_r) \times E \tag{3.6}
\]
\[
E = k_e \omega_r \tag{3.7}
\]

Where \( k_e \) is back-EMF constant, \( f_{abc}(\theta_r) \) are the function of rotor position.
Figure 3.3: Trapezoidal back EMF and phase current waveforms of BLDC motor drive

Figure 3.3 represent the back-EMF is a function of rotor position ($\theta_r$) and has the amplitude $E = k_e \omega_r$. Based on the rotor position, the expression of the back-EMF can be generated as equation (4), (5) and (6) where named as trapezoidal shape functions with limit values between +1 and -1

\[
f_a(\theta_r) = \begin{cases} 
\frac{6}{\pi} \theta_r & (0 < \theta_r < \pi/6) \\
1 & (\pi/6 < \theta_r < 5\pi/6) \\
-(\frac{6}{\pi}\theta_r + 6) & (5\pi/6 < \theta_r < 7\pi/6) \\
-1 & (7\pi/6 < \theta_r < 11\pi/6) \\
(\frac{6}{\pi}\theta_r - 12) & (11\pi/6 < \theta_r < 2\pi) 
\end{cases}
\]

(3.8)

\[
f_b(\theta_r) = \begin{cases} 
-1 & (0 < \theta_r < \pi/6) \\
\frac{6}{\pi} \theta_r - 4 & (\pi/6 < \theta_r < 5\pi/6) \\
1 & (5\pi/6 < \theta_r < 7\pi/6) \\
-(\frac{6}{\pi}\theta_r + 10) & (7\pi/6 < \theta_r < 11\pi/6) \\
-1 & (11\pi/6 < \theta_r < 2\pi) 
\end{cases}
\]

(3.9)
\[
\begin{align*}
fe(\theta_r) &= \begin{cases} 
1 & (0 < \theta_r \ll \pi/6) \\
-(6/\pi)\theta_r + 2 & (\pi/6 < \theta_r \ll 5\pi/6) \\
1 & (5\pi/6 < \theta_r \ll 7\pi/6) \\
(6/\pi)\theta_r - 8 & (7\pi/6 < \theta_r \ll 11\pi/6) \\
1 & (11\pi/6 < \theta_r \ll 2\pi) 
\end{cases} 
\end{align*}
\] (3.10)

The electromagnetic torque is defined by using back-EMFs as follows

\[
T_a = \frac{e_a i_a}{\omega_r} 
\] (3.11)

\[
T_b = \frac{e_b i_b}{\omega_r} 
\] (3.12)

\[
T_c = \frac{e_c i_c}{\omega_r} 
\] (3.13)

Based on the expression of rotor position, the model of back-EMF is shown in Figure 3.4.

![Simulink diagram of generating back EMF from rotor position](image)

Figure 3.4: Simulink diagram of generating back EMF from rotor position

The speed and electromagnetic torque of BLDC motor can be defines as

\[
\omega_m = \frac{P}{2J} \int (T_e - T_L) \, dt = \frac{P}{2J} \int [(T_a + T_b + T_c) - T_L] \, dt 
\] (3.14)
3.2.2.2 Voltage Source Inverter (VSI)

As shown in Figure 3.2, only the two phases are excited through the conduction operating modes. Therefore, three-phase currents are considered in terms of the line-to-line voltages. The following voltage and current equations can be obtained

\[
V_{ab} = 2R_i + 2(L - M) \frac{di}{dt} + e_{ab} \quad \text{(3.15)}
\]
\[
V_{bc} = 2R_i + 2(L - M) \frac{di}{dt} + e_{bc} \quad \text{(3.16)}
\]
\[
V_{ca} = 2R_i + 2(L - M) \frac{di}{dt} + e_{ca} \quad \text{(3.17)}
\]

Where

\[
i_1, i_2, i_3 \quad \text{= Loops current}
\]
\[
e_{ab}, e_{bc}, e_{ca} \quad \text{= The line-to-line back EMFs}
\]

The line-to-line back EMFs can be derived as

\[
e_{ab} = e_a - e_b \quad \text{(3.18)}
\]
\[
e_{bc} = e_b - e_c \quad \text{(3.19)}
\]
\[
e_{ca} = e_c - e_a \quad \text{(3.20)}
\]

Meanwhile the phase current can be expressed as

\[
i_a = i_1 - i_3 \quad \text{(3.21)}
\]
\[
i_b = i_2 - i_1 \quad \text{(3.22)}
\]
\[
i_c = i_3 - i_2 \quad \text{(3.23)}
\]

Using the switching function \( V_{abc} \) which is obtained from hysteresis block, \( v_{ao}, v_{bo} \) and \( v_{co} \) in reference to midpoint of DC supply voltage \( V_{dc} \) can be calculated as

\[
v_{ao} = \frac{V_d}{2} V_a = \frac{V_d}{2} \sum_{0}^{\infty} A_n \sin(n \omega t) \quad \text{(3.24)}
\]
\[
v_{bo} = \frac{V_d}{2} V_b = \frac{V_d}{2} \sum_{0}^{\infty} A_n \sin[n(\omega t - 120)] \quad \text{(3.25)}
\]
\[ v_{ce} = \frac{V_d}{2} v_c = \frac{V_d}{2} \sum_{n=0}^{\infty} A_n \sin[n(\omega t - 240)] \]

(3.26)

Then the inverter line-to-line voltage can be derived as

\[ V_{ab} = V_{ao} - V_{bo} \]  
(3.27)
\[ V_{bc} = V_{bo} - V_{co} \]  
(3.28)
\[ V_{ca} = V_{co} - V_{ao} \]  
(3.29)

The simulation block of the current equations is shown in Figure 3.5.

![Simulink diagram of three-phase currents](image)

Figure 3.5: Simulink diagram of three-phase currents

### 3.2.2.3 Reference Current Generator

The motor reference phase currents can be determined based on the reference current generator by considering reference current amplitude \( I_{max} \), where it can be
calculated depending on rotor position \( (\Theta_r) \). The reference current amplitude \( (I_{\text{max}}) \) can be obtained as

\[
I_{\text{max}} = \frac{u}{k_t}
\]  
(3.30)

where \( u \) is the control signal archived from neural network controller and \( k_t \) is the torque constant of the BLDC motor. Figure 3.6 represented the reference phase current where the function \( i_{abc\_\text{ref}} \) is defined according to Table 1. All the current will be an input to the PWM current control block.

![Simulink diagram of reference currents block](image)

Figure 3.6: Simulink diagram of reference currents block

The reference current \( (i_{a\text{ref}}, i_{b\text{ref}}, i_{c\text{ref}}) \) in PWM current control block are compared with the motor’s actual phase current \( (i_a, i_b \text{ and } i_c) \) and the current errors are calculated in the equation (3.31), (3.32) and (3.33). These errors are applied to inverter hysteresis and the switching signal of PWM inverter system are generated based on the switching states. Figure 3.6 referring the hysteresis current control is presented in function block \( i_{abc\_\text{ref}} \) by considering the measured phase current \( i_a \), the reference current \( I_{\text{max}} \) and the rotor position \( (\Theta_r) \).

\[
e_{ia} = i_{a\text{ref}} - i_a
\]  
(3.31)

\[
e_{ib} = i_{b\text{ref}} - i_b
\]  
(3.32)

\[
e_{ic} = i_{c\text{ref}} - i_c
\]  
(3.33)
Table 3.1: Reference currents of BLDC motor

<table>
<thead>
<tr>
<th>Rotor position (θ-Degree)</th>
<th>Reference current (A)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$i_{\sigma ref}$</td>
</tr>
<tr>
<td>0 – 30</td>
<td>0</td>
</tr>
<tr>
<td>30 – 90</td>
<td>Imax</td>
</tr>
<tr>
<td>90 – 150</td>
<td>Imax</td>
</tr>
<tr>
<td>150 – 210</td>
<td>0</td>
</tr>
<tr>
<td>210 – 270</td>
<td>-Imax</td>
</tr>
<tr>
<td>270 – 330</td>
<td>-Imax</td>
</tr>
<tr>
<td>330 – 360</td>
<td>0</td>
</tr>
</tbody>
</table>
The flow chart below represents the process involved during the BLDC simulation model as shown in Figure 3.7.

![Flow Chart Image]

Figure 3.7: The flow chart of BLDC motor simulation model.
3.3 Neural Structure and Learning Scheme

3.3.1 Structure of Neural Network Controller

To design the neural network control, some information about the plant is required. Basically, the numbers of input and output neuron at each layer are equal to the number of input and output signals of the system respectively. The structure of the proposed neural network control of a BLDC motor is as shown in Figure 3.8. Based on the number of neurons in each layer of the proposed NNC architecture, the network has a 2-3-1 structure. In the input layer consists of two input neurons. The first input neuron is error signal between desired signal and actual signal. The second input neuron is different between previous error signal and current error signal.

![Diagram of neural network controller](image)

Figure 3.8: Architecture of the proposed neural network controller

The connections weight parameter between \( j_{th} \) and \( i_{th} \) neuron at \( m_{th} \) layer is given by \( w_{ij} \), while bias parameter of this layer at \( i_{th} \) neuron is given by \( b_{mi} \). Transfer function of the network at \( i_{th} \) neuron in \( m_{th} \) layer is defined as

\[
    n_i^m = \sum_{j=1}^{5^{m-1}} w_{ij} a_j^{m-1} + b_i^m
\]

(3.34)

The output function of neuron at \( m^{th} \) layer is given by

\[
    a_i^m = f^m(n_i^m)
\]

(3.35)