CHAPTER 4

FUZZY TUNED PID SUPERVISED OFFLINE ADAPTIVE NEURO FUZZY INFERENCE SYSTEM BASED CONTROLLER FOR BRUSHLESS DC MOTOR

4.1 INTRODUCTION

In this chapter, fuzzy tuned PID offline Adaptive Neuro Fuzzy Inference System (ANFIS) based speed controller is presented for Brushless DC motor. The overall speed control system is simulated and validated using MATLAB/Simulink toolbox. Offline ANFIS controller is modelled through modified input and output training data collected from fuzzy tuned PID controller. The effectiveness of controller is validated for different operating conditions of the Brushless DC motor such as constant load conditions, varying load conditions and varying set speed conditions.

Fuzzy tuned PID supervised offline ANFIS controller is compared with classical Proportional Integral (PI) controller, Fuzzy Variable Structure controller (FVS), and Fuzzy Tuned PID controller. For effective comparisons of the controllers, the following performance parameters such as rise time, settling time, recovery time, peak overshoot, undershoot, and steady state error are measured and analyzed for the above considered controllers.

4.2 ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) BASED CONTROLLER

The general ANFIS control structure contains the same components as the FIS except for the neural network block. The structure of the network is composed of set of units (and connections) arranged in five connected network layers i.e., layer1 to layer 5. The ANFIS controller structure consists of four important blocks that are
fuzzification, knowledge base, neural network and the defuzzification. The detail about each layer is given below.

Layer 1 consists of input variables (membership functions) and triangular or bell shaped membership functions.

Layer 2 is membership layer and it checks for the weights of each membership functions. It receives the input values from the first layer and act as membership functions to represent the fuzzy sets of the respective input variables.

Layer 3 is called as rule layer and it receives input from the previous layer. Each node (each neuron) in this layer performs the pre-condition matching of the fuzzy rules. This layer computes the activation level of each rule and the number of layers equals to the number of fuzzy rules. Each node of this layer calculates the weights which will be normalized.

Layer 4 is the defuzzification layer which provides the output values resulting from the inference of rules.

Layer 5 is called as the output layer which sums up all the inputs coming from the layer 4 and transforms the fuzzy classification results into a crisp value (Mohamed A et al 2009).

ANFIS modelled by Takagi-Sugeno (T-S) type systems are considered and it must have the following properties: It must be first or zero order T-S type system. It should have a single output, obtained using weighted average defuzzification. All output membership functions must be of the same type and it must be either linear or constant. It must have no rule sharing, i.e., different rules cannot share the same output membership function. The number of output membership functions must be equal to the number of rules. It must have unity weight for each rule. The ANFIS structure is tuned automatically by least-square estimation and the back propagation
algorithm. Because of its flexibility, the ANFIS strategy can be used for a wide range of control applications.

The algorithm presented above is used in the proceeding section to develop the fuzzy tuned PID supervised offline ANFIS controller for controlling the speed of Brushless DC motor.

## 4.3 FUZZY TUNED PID SUPERVISED OFFLINE ANFIS CONTROL SCHEME FOR SPEED CONTROL OF BRUSHLESS DC MOTOR

The development of the control strategy for speed control of Brushless DC motor with offline ANFIS controller is presented in Figure 4.1.

![Figure 4.1 Offline ANFIS controller for Brushless DC motor](image)

It consists of two loops namely inner loop and outer loop. Inner loop is used for synchronizing the inverting gate signal with back electro motive force or rotor position of the motor. The outer loop is used for controlling the speed of the Brushless DC motor by controlling the dc bus voltage through pulse width modulated (PWM) inverter. Based upon error and rate of change of error, offline ANFIS controller provides the control signal to the switching logic circuit. The switching logic circuit provides the PWM signal for the inverter gate with respect to rotor
position of the motor and the control signal output obtained from offline ANFIS controller.

ANFIS incorporates artificial neural network with fuzzy inference system and first-order Takagi Sugeno fuzzy model is used in this work. The analysis has two inputs, error (e), rate of change of error (Δe) and the output is control signal. The if-then rules are given in equation (4.1) as,

**Rule 1**: IF e is $A_1$; Δe is $B_1$; then $f_1 = P_1 e + R_1 \Delta e + s_1$

**Rule 2**: IF e is $A_1$; Δe is $B_2$; then $f_2 = P_2 e + R_2 \Delta e + s_2$

\[ \vdots \]

**Rule i-1**: IF e is $A_j$; Δe is $B_{j-1}$; then $f_{i-1} = P_{i-1} e + R_{i-1} \Delta e + s_{i-1}$

**Rule i**: IF e is $A_j$; Δe is $B_j$; then $f_i = P_i e + R_i \Delta e + s_i$

(4.1)

Where,

\[ e = \omega_{ref} - \omega_r \]  
(4.2)

\[ \Delta e = \frac{d(\omega_{ref} - \omega_r)}{dt} \]  
(4.3)

\[ f_i = P_i e + R_i \Delta e + s_i \]  
(4.4)

$\omega_{ref}$ is the reference speed, $\omega_r$ is the actual rotor speed, $j=1, 2, \ldots, q$, $i=1, 2, \ldots, q^2$, $A$ and $B$ are the fuzzy membership sets defined for input variables $e$ and $\Delta e$. $q$ is the number of membership functions for the fuzzy systems of inputs $e$ and $\Delta e$. $f_i$ is the linear consequent functions defined in terms of inputs $e$ and $\Delta e$. $P_i$, $R_i$ and $s_i$ are consequent parameters of an ANFIS fuzzy model. Same-layer nodes of an ANFIS model have similar functions. Output signals from the nodes of a preceding layer are the input signals to the next layer. The structure of five layer ANFIS is shown in Figure 4.2 as the details about the action performed in each layer is presented under section 4.2.
The error and rate of change of error i.e., $e$ and $\Delta e$ as mentioned in the equation (4.2) and (4.3) are given as input to layer 1. In Membership layer which is termed as layer 1, every node is an adaptive node with a particular fuzzy membership function specifying the degrees of the inputs which satisfies the quantifier. Equation (4.5) represents the node outputs for the two inputs.

$$L_{1,j} = \mu A_j(e) \quad \text{for } j = 1,2,\ldots,q$$
$$L_{1,j} = \mu B_j(\Delta e) \quad \text{for } j = 1,2,\ldots,q \quad (4.5)$$

The membership functions considered for $A$ and $B$ in the equation (4.5) are triangular-shaped functions and their representations are given in the equations (4.6) and (4.7).

$$\mu A_j(e, a_j, b_j, c_j) = \begin{cases} 0, & e \leq 0 \\ \frac{e-a_j}{b_j-a_j}, & a_j \leq e \leq b_j \\ \frac{c_j-e}{c_j-b_j}, & b_j \leq e \leq c_j \\ 0, & c_j \leq e \end{cases} \quad (4.6)$$
The parameters for fuzzy membership functions are \(a_j, b_j, c_j, x_j, y_j\) and \(z_j\). The triangular-shaped function changes its pattern with corresponding changes in the parameters. This change will provide various contours of the triangular-shaped function in accordance with the data set for the problem considered. Parameters in this layer are known as premise parameters.

In Product layer which is termed as layer 2, every node is a fixed node labeled ‘\(\alpha\)’. \(L_{2,i}\) output is the product of all incoming signals and it is given in the equation (4.8).

\[
L_{2,i} = W_i = \begin{bmatrix}
W_1 & \cdots & W_q \\
\vdots & \ddots & \vdots \\
W_{q^2-(q-1)} & \cdots & W_{q^2}
\end{bmatrix} = \begin{bmatrix}
\mu A_1 * \mu B_1 & \cdots & \mu A_1 * \mu B_q \\
\vdots & \ddots & \vdots \\
\mu A_q * \mu B_1 & \cdots & \mu A_q * \mu B_q
\end{bmatrix}
\] (4.8)

Each of the second layer’s node output represents the firing strength of the associated rule. The T-norm operator algebraic product (\(T_{AB} (A, B) = A*B\)) is used to obtain the firing strength (\(W_i\)).

In normalization layer which is termed as layer 3, every node is a fixed node labeled “\(N\)”. The output of the \(i^{th}\) node is the ratio of the firing strength of the \(i^{th}\) rule (\(W_i\)) to the sum of the firing strength of all the rules and it is given in equation (4.9).

\[
L_{3,i} = \overline{W_i} = \frac{W_i}{\sum_{i=1}^{q^2} W_i}
\] (4.9)

This output gives a normalized firing strength.
In rule layer which is termed as layer 4, every node is an adaptive node with a node function given by the equation (4.10).

\[
L_{4,i} = \overline{W}_i f_i = \overline{W}_i (P_i e + R_i \Delta e + s_i) 
\]  

(4.10)

\( \overline{W}_i \) is the normalized firing strength from layer 4 and \( P_i, R_i \), and \( s_i \) are the control signal parameter sets of this node. Parameters in this layer are known as consequent parameters.

In output layer which is termed as layer 5, the single node is a fixed node labeled ‘\( \Sigma \)’. It computes the overall output as the summation of all incoming signals and it is given in equation (4.11).

\[
L_{5,1} = \sum_i \overline{W}_i f_i = \frac{\sum_i \overline{W}_i f_i}{\sum_i \overline{W}_i} 
\]  

(4.11)

Next, the process of applying hybrid learning algorithm to identify ANFIS parameters has been discussed. For the learning process, the initial input membership function and number of rules for fuzzy inference system for the input-output training data sets should be specified. Basically, the number of membership function assigned to each input variable is chosen experimentally i.e., by plotting the data sets and examining them visually or simply by trial and error approach. For data sets with more than one input, visualization techniques are not very effective and one has to rely on trial and error approach. But trial and error method is time consuming process, and to overcome this difficulty, clustering methods such as grid partition clustering, subtractive clustering, etc. are employed.

In this work, the grid partition clustering methods are used for generating the initial membership function and number of fuzzy rules for input-output training data sets. In grid partition, the number of memberships on each input variable uniquely determines the number of rules. There are two inputs and seven memberships on each input which has resulted in \( 7^2 = 49 \) fuzzy if-then rules. Hybrid learning algorithm combines the gradient descent and the least squares estimation for the fast identification of premise and consequent parameters of ANFIS.
Each iteration comprises of a forward pass and a backward pass sequence. In forward pass, after an input data is presented, the node outputs are updated layer by layer until layer 4 is reached. This process is repeated for all training input-output data sets, and then the consequent parameters are identified by least squares estimation. In backward pass, the derivative of the error signals with respect to each node propagates from the output end toward the input end. Then the gradient vector is accumulated for each training input-output data set. At the end of the backward pass for all training data sets, the premise parameters are updated by gradient descent method. Once updating of premise and consequent parameters are completed, proper set of membership function and rule base are selected for fuzzy inference system. After proper rules are selected and fired, the control signal required to obtain the optimal output is generated.

To train the ANFIS controller, the network is trained in off-line using MATLAB simulink tool box. To start with, the result of fuzzy tuned PID controller is collected as the training data set. The input and output data obtained are modified into desired data based upon the desired output. The desired output will be trained using the function ‘ANFIS’ in the MATLAB toolbox. From the training, a fuzzy inference system with adjusted membership functions has been obtained.

4.4 DEVELOPMENT OF SIMULINK MODEL AND TRAINING OF FUZZY TUNED PID SUPERVISED OFFLINE ANFIS CONTROLLER USING MATLAB

Simulink model for the control of Brushless DC motor drive has been developed in MATLAB environment using the appropriate tool boxes. Figure 4.3 shows the simulink model of the fuzzy tuned PID supervised offline ANFIS controller for Brushless DC motor.

The simulink model consists of DC supply, PWM inverter, motor measurement system, ANFIS controller, switching logic circuit and Brushless DC motor. The DC supply input is given to PWM inverter and output of the inverter is fed
to the Brushless DC motor. Rotor position and speed are sensed by hall sensor and tachogenerator model. The output of the tachogenerator is compared with reference speed to produce speed error and the rate of change of speed error is obtained by differentiating the speed error. The speed error and the rate of change of speed error are given as input to the offline ANFIS speed controller. Based upon the inputs, offline ANFIS controller generates control signal for the switching logic circuit. The switching logic circuit generates gating signals based upon the rotor position and control signal received from the offline ANFIS controller. This gating signal is used for triggering the IGBT of the PWM inverter. By this process, DC bus voltage is controlled which in turn controls the speed of the Brushless DC motor.

Figure 4.3 Simulink model of fuzzy tuned PID supervised offline ANFIS controller for Brushless DC motor

In order to start the simulations, first step is the identification process i.e., the dynamic process of finding the input – output relations for a system. Figure 4.4 shows the block diagram for the identifier. In the identifier, the process of clustering involves the determination of clusters in data space and the translation of these
clusters into fuzzy rules such that the model obtained is very close to the identified system. Identification process of the offline ANFIS controller is modelled through modified input and output data of fuzzy tuned PID controller. To prevent the system from possible saturation condition, the input-output data set is processed through closed loop using fuzzy tuned PID controller. Two inputs to the offline ANFIS based identifier are the input error signal $e$ and rate of change of error $\Delta e$ of the Brushless DC motor. The problem is to find the proper parameter values for the offline ANFIS structure and control signal for the switching logic circuit to minimize identifier output error for all input values of $e$ and $\Delta e$.

**Figure 4.4 Block diagram for identification process of offline ANFIS controller**

The period of identifier reference signal is $9\times10^4$ samples and the mathematical expression for the identifier reference signal is given in equation (4.12). Using equations (4.12) and (4.13), the identifier reference signal is modified to obtain desired output signal. Figure 4.5 shows the modified training data for the offline ANFIS controller.
\[ U(x) = \begin{cases} \frac{(1.2\times10^4)\times(1550-x)}{1540}, & \text{if } 0 < x \leq 1540 \\ 10, & \text{if } 1540 < x \leq 23400 \\ 50, & \text{if } 23400 < x \leq 47500 \\ 
\frac{(6\times10^4)\times(x-47795)}{47795}, & \text{if } 47500 < x \leq 48000 \\ 25, & \text{if } 48000 < x \leq 90000 \end{cases} \]

\[ m(x) = \begin{cases} -x \times \frac{10}{47500}, & \text{if } 0 < x \leq 47500 \\ x \times \frac{10}{47500}, & \text{if } 47500 < x \leq 90000 \end{cases} \]

\[ U_m(x) = \begin{cases} \frac{(1.2\times10^4)\times(1550-x+m(x))}{1540}, & \text{if } 0 < x \leq 1540 \\ 10 + m(x), & \text{if } 1540 < x \leq 23400 \\ 50 + m(x), & \text{if } 23400 < x \leq 47500 \\ \frac{(4\times10^4)\times(x-47795+m(x))}{47795}, & \text{if } 47500 < x \leq 48000 \\ 25 + m(x), & \text{if } 48000 < x \leq 90000 \end{cases} \]

Where, \( U(x) \) is the actual reference signal data collected from fuzzy tuned PID controller and \( m(x) \) is the modification data which will be added to the actual reference signal to produce desired data. \( U_m(x) \) is the modified reference signal data of the fuzzy tuned PID controller to train the offline ANFIS controller.

Initially input – output membership function and 49 fuzzy rule set have to be invoked from the grid partition of ANFIS concept. The initial rule base for T-S fuzzy inference system is shown in Figure 4.6 and initial input membership function is provided in Table 4.1.
Figure 4.5 Modified training data for offline ANFIS controller

Figure 4.6 Initial rule base for T-S fuzzy inference system
Table 4.1 Initial input membership function

<table>
<thead>
<tr>
<th>Distribution of membership function</th>
<th>$A_j$ or $e$</th>
<th>$B_j$ or $\Delta e$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_j$</td>
<td>$b_j$</td>
<td>$c_j$</td>
</tr>
<tr>
<td>1</td>
<td>-830</td>
<td>-497.1</td>
</tr>
<tr>
<td>2</td>
<td>-497.1</td>
<td>-164.3</td>
</tr>
<tr>
<td>3</td>
<td>-164.3</td>
<td>168.6</td>
</tr>
<tr>
<td>4</td>
<td>168.6</td>
<td>501.4</td>
</tr>
<tr>
<td>5</td>
<td>501.4</td>
<td>834.3</td>
</tr>
<tr>
<td>6</td>
<td>834.3</td>
<td>1167</td>
</tr>
<tr>
<td>7</td>
<td>1167</td>
<td>1500</td>
</tr>
</tbody>
</table>

After generating the initial input membership function and fuzzy rules based on the modified training data, fuzzy inference system is trained by the hybrid learning algorithm of neural network.

![Training Error Plot](image)

**Figure 4.7 Training error plot**

Ten epochs have been considered for training and Figure 4.7 shows training error at the end of training. From the training error plot, it is evident that the fuzzy inference system has been well trained with help of neural network with minimum error of 1.824.
Figure 4.8 Testing of trained data with test data

Figure 4.9 Final rule base for T-S fuzzy inference system

Figure 4.8 shows the testing of trained data with test data. After the training, final rule base for fuzzy inference system is generated and it is shown in Figure 4.9.
Figure 4.10 Offline ANFIS model structure for Brushless DC motor

Figure 4.10 shows the offline ANFIS model structure. The structure consists of five layers as explained under section 4.2. First layer is the input layer and the inputs are error and rate of change of error. Next layer is the input membership function layer and inputs are distributed with seven fuzzy sets. Third layer is the rule layer where the inputs and outputs are linked with AND operator. Fourth layer is the output membership function layer where the output has been distributed with forty nine constant values. Last layer is the output layer which sums up all the inputs coming from the previous layer and transforms the fuzzy classification results into a crisp value.

4.4.1 Simulation results and discussion

To validate the developed control strategies described above, simulation has been carried out for the Brushless DC motor drive system using MATLAB/SIMULINK. The specifications used for the Brushless DC motor drive system is given in the following Table 4.2.
Table 4.2 Specifications of Brushless DC motor drive

<table>
<thead>
<tr>
<th>Specifications</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated Voltage (Volts)</td>
<td>470</td>
</tr>
<tr>
<td>Rated Current (Amps)</td>
<td>50</td>
</tr>
<tr>
<td>Rated Speed (rpm)</td>
<td>1500</td>
</tr>
<tr>
<td>Stator phase resistance R (ohm)</td>
<td>3</td>
</tr>
<tr>
<td>Stator phase inductance L (H)</td>
<td>0.001</td>
</tr>
<tr>
<td>Flux linkage established by magnets (V-sec)</td>
<td>0.175</td>
</tr>
<tr>
<td>Voltage Constant (V/rpm)</td>
<td>0.1466</td>
</tr>
<tr>
<td>Torque Constant (N-m / A)</td>
<td>1.4</td>
</tr>
<tr>
<td>Moment of Inertia (kg-m²/rad)</td>
<td>0.0008</td>
</tr>
<tr>
<td>Friction factor (N-m/(rad/sec))</td>
<td>0.001</td>
</tr>
<tr>
<td>Pole pairs</td>
<td>4</td>
</tr>
</tbody>
</table>

Figure 4.11 (a) Phase voltage waveforms based on the rotor position at 1500 rpm, (b) Phase current waveforms based on the rotor position at 1500 rpm

Figure 4.11 (a) shows the phase voltage waveforms based on the rotor position at 1500 rpm. The phase difference between $V_a$, $V_b$ and $V_c$ is approximately $120^\circ$. Figure 4.11 (b) shows the simulation result of the phase current waveforms based on the rotor position at 1500 rpm. The peak current value is approximately 50 amperes for all $I_a$, $I_b$ and $I_c$. 
4.4.1.1 Response of the motor for constant load condition

Simulation results of speed response of Brushless DC motor using fuzzy variable structure, fuzzy tuned PID, classical PI controller and fuzzy tuned supervised offline ANFIS controllers are shown in Figure 4.12.

![Figure 4.12 Speed response of Brushless DC motor for four controllers](image)

The simulation result has been obtained by keeping the reference speed at 1500 rpm and the load torque constant at 25 Nm. From the response plots shown above, for the PI controller, the drive attains the set or reference speed in 1 second. If the fuzzy variable structure controller is used, reference speed is reached in 0.1 second and it is only 0.064 second for fuzzy tuned PID controller and 0.0611 second for fuzzy tuned PID supervised offline ANFIS controller. Also, the other response parameters such as rise time, peak overshoot, settling time, steady state error and percentage of steady state error are compared for different controllers and presented in Table 4.3.
Table 4.3 Comparison of response parameters for constant load condition

<table>
<thead>
<tr>
<th>Controller</th>
<th>Rise time (sec)</th>
<th>Peak value (rpm)</th>
<th>% peak overshoot</th>
<th>Peak time (sec)</th>
<th>Settling time (sec)</th>
<th>Steady state error (rpm)</th>
<th>% steady state error</th>
</tr>
</thead>
<tbody>
<tr>
<td>PI</td>
<td>0.255</td>
<td>-</td>
<td></td>
<td>1</td>
<td>8</td>
<td>0.54</td>
<td></td>
</tr>
<tr>
<td>FVS</td>
<td>0.092</td>
<td>1510.5</td>
<td>0.7</td>
<td>0.0923</td>
<td>0.1</td>
<td>3.5</td>
<td>0.24</td>
</tr>
<tr>
<td>Fuzzy tuned PID</td>
<td>0.048</td>
<td>1506</td>
<td>0.4</td>
<td>0.0541</td>
<td>0.064</td>
<td>3</td>
<td>0.2</td>
</tr>
<tr>
<td>Fuzzy tuned PID offline ANFIS</td>
<td>0.05</td>
<td>1511</td>
<td>0.73</td>
<td>0.0528</td>
<td>0.0611</td>
<td>1.5</td>
<td>0.1</td>
</tr>
</tbody>
</table>

From the results shown above, all the vital performance indexes are in favour of fuzzy tuned PID offline ANFIS controller only. With the newly developed controller, the Brushless DC drive system will have superior rise time, steady state error and settling time characteristics.

4.4.1.2 Response of the drive under varying load conditions

Any drive, as most of the application demands, it has to perform under varying load conditions. Therefore, in order to ascertain the superior performance of the fuzzy tuned PID supervised offline ANFIS controller, simulation results has been obtained for varying load conditions also.

First, the load torque is decreased from 25 Nm to 15 Nm and then it is increased from 25 Nm to 35 Nm. The Figure 4.13 & 4.14 shows the response obtained for varying load conditions.
The important parameters such as percentage peak overshoot, percentage peak undershoot and steady state error has been compared for the above controllers and the results are presented in Table 4.4. Following sudden load change, any system
will take sufficient time to adjust before tracking and settling at set speed. This is termed as recovery time and it becomes the testing ground for judging the performance of any controller. A good controller should be able to restore the system to set value in the shortest possible time following any disturbance. The recovery time also is compared for all controllers and presented below. Case A represents decrease in load torque from 25 Nm to 15 Nm and Case B represents increase in load torque from 25 Nm to 35 Nm.

Table 4.4 Comparison of response parameters for varying load conditions

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Load conditions</th>
<th>PI Controller</th>
<th>FVS controller</th>
<th>Fuzzy tuned PID</th>
<th>Fuzzy tuned PID supervised offline ANFIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>% peak overshoot</td>
<td>Case A</td>
<td>9.5</td>
<td>0.17</td>
<td>0.24</td>
<td>0.13</td>
</tr>
<tr>
<td>% peak undershoot</td>
<td>Case B</td>
<td>14</td>
<td>0.54</td>
<td>1.13</td>
<td>0.33</td>
</tr>
<tr>
<td>Steady state error (rpm)</td>
<td>Case A</td>
<td>8</td>
<td>3.5</td>
<td>2.5</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Case B</td>
<td>20</td>
<td>6</td>
<td>18</td>
<td>3</td>
</tr>
<tr>
<td>Recovery time (sec)</td>
<td>Case A</td>
<td>1.8</td>
<td>0</td>
<td>0.52</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Case B</td>
<td>2</td>
<td>0</td>
<td>0.65</td>
<td>0</td>
</tr>
</tbody>
</table>

From the results, it is clear that, the fuzzy tuned PID supervised offline ANFIS controller for the Brushless DC motor drive is superior in all aspects when compared with other controllers. When the load is increased or decreased, the fuzzy tuned PID supervised offline ANFIS controller does not produce any undershoot or overshoot. Also, zero recovery time indicates that, the proposed controller is very well suited for the drives employed for varying load conditions.
4.4.1.3 Response of the drive for step change in reference speed

In a process system, the drive may be required to operate at varying speed conditions. To validate the suitability of the controller for varying speed conditions, as it is the realistic one, the response is obtained for step change in speed also.

Figure 4.15 Comparison of controllers performance - speed change from 1500 rpm to 1000 rpm

Figure 4.16 Comparison of controllers performance - speed change from 1000 rpm to 1500 rpm

First, the set speed is changed from 1500 rpm to 1000 rpm (Case A) and then from 1000 rpm to 1500 rpm (Case B). The response characteristics obtained
through simulation for the different controllers are shown in Figure 4.15 & 4.16. The important parameters to be measured following step change in speed i.e., steady state error and recovery time are measured and shown in Table 4.5.

**Table 4.5 Comparison of response parameters for change in set speed conditions**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Speed conditions</th>
<th>PI Controller</th>
<th>FVS controller</th>
<th>Fuzzy tuned PID</th>
<th>Fuzzy tuned PID offline ANFIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Steady state error (rpm)</td>
<td>Case A</td>
<td>10</td>
<td>2.5</td>
<td>10</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Case B</td>
<td>20</td>
<td>5</td>
<td>20</td>
<td>3</td>
</tr>
<tr>
<td>Recovery time (sec)</td>
<td>Case A</td>
<td>1.8</td>
<td>0.61</td>
<td>0.53</td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td>Case B</td>
<td>1.9</td>
<td>0.6</td>
<td>0.55</td>
<td>0.54</td>
</tr>
</tbody>
</table>

Steady state error and recovery time measured are in favour of fuzzy tuned PID supervised offline ANFIS controller only. The fuzzy tuned PID supervised offline ANFIS controller for Brushless DC motor drive is performing very well under change in reference speed conditions also when compared with other controllers.

### 4.5 SUMMARY

Fuzzy tuned PID supervised offline ANFIS controller have been presented for the speed control of Brushless DC motor. The control system parameters are obtained for the proposed controller and compared with proportional integral controller, fuzzy variable structure controller and fuzzy tuned PID controller. In order to test the effectiveness of the controllers under realistic operating environment, various operating conditions such as constant load, varying load and varying set speed conditions are considered and the performances are observed. From the parameters considered for comparison, it has been ascertained that, the fuzzy tuned PID supervised offline ANFIS controller clearly outperforms the other controllers under all considered operating conditions of the Brushless DC motor and it is the best of all. It can be readily implemented for speed control of Brushless DC motor.