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Adaptive Neuro-Fuzzy Inference System based speed controller for brushless DC motor

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ABSTRACT

In this paper, a novel controller for brushless DC (BLDC) motor has been presented. The proposed controller is based on Adaptive Neuro-Fuzzy Inference System (ANFIS) and the rigorous analysis through simulation is performed using simulink tool box in MATLAB environment. The performance of the motor with proposed ANFIS controller is analyzed and compared with classical Proportional Integral (PI) controller, Fuzzy Tuned PID controller and Fuzzy Variable Structure controller. The dynamic characteristics of the brushless DC motor is observed and analyzed using the developed MATLAB/simulink model. Control system response parameters such as overshoot, undershoot, rise time, recovery time and steady state error are measured and compared for the above controllers. In order to validate the performance of the proposed controller under realistic working environment, simulation result has been obtained and analyzed for varying load and varying set speed conditions.

1. Introduction

Brushless DC (BLDC) motors are coming of age due to continuous improvement in high energy permanent magnet materials, power semiconductor and digital integrated circuits. In any application requiring an electric motor where the space and weight are at a premium, the BLDC motors becomes the ideal choice. A BLDC motor has high power to mass ratio, good dissipation characteristics and high speed capabilities. Limitations of brushed DC motors overcome by BLDC motors include lower efficiency, susceptibility of the commutator assembly to mechanical wear, consequent need for servicing, less ruggedness and requirement for more expensive control electronics. Due to their favorable electrical and mechanical properties, BLDC motors are widely used in servo applications such as automotive, aerospace, medical field, instrumentation areas, electromechanical actuation systems and industrial automation requirements [1–3]. Many control schemes have been developed for improving the performance of BLDC motor drives.

Many varieties of control schemes such as Proportional Integral Derivative (PID), Non-Adaptive Fuzzy Logic Controller (FLC) and Adaptive Fuzzy Logic Controller have been developed for the speed control of brushless DC motors. Most of the manufacturing processes still use the conventional PID controllers due to their simplicity and robust design. Conventional PID controllers are usually not efficient if the processes involved are of higher order and time delay systems, non-linear systems, complex and unclear systems without accurate mathematical models and systems with uncertainties [4,5].

Non-adaptive fuzzy logic, which is based on fuzzy set theory, was first developed by Zadeh in 1965. Control applications such as temperature control, traffic control, DC motor speed control, etc. are the most prevalent of non-adaptive fuzzy logic applications. For the most complex systems, where few numerical data exist and where only ambiguous or imprecise information is available, fuzzy reasoning provides a way to understand the system behavior by allowing interpretation between the observed input and the output relations of the system [6–9]. While non-adaptive fuzzy control has proven its value in some applications, it is sometimes difficult to state the rule base for some plants, or the need could arise to tune the rule-base parameters if the plant changes. In order to overcome these shortcomings, adaptive fuzzy logic speed controller has been developed [10–20].

In this paper, an attempt has been made to improve the performance of speed controller by proposing a novel ANFIS speed controller for BLDC motor drive. The paper is organized as follows: Literature review is given in Section 2 and mathematical model of the BLDC motor drive is presented in Section 3. Adaptive Neuro-Fuzzy Inference

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System based controller is presented in Section 4 and Section 5 discusses simulation results. Concluding remarks is outlined in Sction 6.

2. Literature review

Fuzzy Proportional Integral based speed controller designed for brushless DC motor exhibits more oscillatory speed response under load varying condition [6]. In [7], simulation results of fuzzy logic based current and speed controller for BLDC motor drive was presented and it has produced more oscillatory speed response. Fuzzy logic controller for BLDC permanent magnet motor drive has been discussed in [8]. From the simulation and experiment results, it has been observed that, during load disturbance, overshoot and undershoot were produced in the speed response. In [9], comparative evaluation between classical PID controller and hybrid fuzzy logic PID controller has been presented. The results proved that fuzzy logic controller outperforms PID controller but speed response obtained during load variations exhibited overshoot and undershoot.

In [10], modified model reference adaptive fuzzy logic speed controller was designed for BLDC motor drive. This controller needs reference plant model for training the fuzzy logic controller and also the response was more oscillatory. Adaptive fuzzy logic speed controller for brushless dc motor drive has been discussed in [11] and this controller has two structures namely fuzzy proportional derivative and fuzzy Proportional Integral controller. Adaptation is made based upon error signal received and this controller cannot be used for other plant models. Adaptive sliding mode controller, non-adaptive fuzzy controller and adaptive fuzzy based controllers have been presented for the BLDC motor drive in [12,13]. But, the simulation and experimental results have clearly indicated that the parameters like steady state error, settling time, overshoot and response time are not in favor of controller performance during load disturbance.

The combination of neural network and fuzzy system has recently become popular in engineering fields and one such structure namely Adaptive Neuro-Fuzzy Inference System was discussed in [14–20]. In [14], intelligent agent based Adaptive Neuro-Fuzzy Inference System (ANFIS) was developed to perform Non-linear Auto-Regressive Moving Average with exogenous input (NARMAX) system identification of BLDC motor. Back electromagnetic force prediction performed by ANFIS for sensorless control of brushless dc motor was presented in [15]. Gain adjustment of dead beat Proportional Integral based speed controller for BLDC motor has been designed by particle swarm with ANFIS [16]. The limitation of this controller is that, it worked only for particular operating conditions. The controller response has changed abruptly for change in operating conditions. Also, the system exhibited larger overshoot, high rise time, high settling time and increased possibility of system moving to unstable state. In [17], hybrid approach was followed for designing the speed controller. The controller incorporates Neuro fuzzy based proportional derivative controller and conventional integral controller. Neuro fuzzy controller produced more noise in the control system and tuning of the integral gain has considerable effect on the control performance such as overshoot and settling time. ANFIS based controller has been designed for brushless dc motor in [18,19], but the speed response exhibited high rise time, high settling time and larger steady state error. In [20], ANFIS controller based on emotional learning algorithm was presented. The emotional learning algorithm utilized the proportional derivative controller function and it modified the output layer gain of Neuro fuzzy controller. But, tuning of the proportional and derivative gains has resulted in large overshoot, large settling time and high steady state error in the system performance.

Fig. 1 shows the controllers considered for investigation. Fig. 1 (a) shows Proportional Integral controller [3]. It is simple and widely used in most of the industries till now but tuning of gain in the proportional and integral part has significant effect on control system performance. Also, performance uncertainty was experienced during load variations. In order to overcome this problem, Non-Adaptive Fuzzy Logic Controller, i.e., Fuzzy Tuned PID controller has been developed and it is shown in Fig. 1(b). The controller design has been carried out on trial and error basis. Also, it required more number of rules, i.e., 147 rules and performance uncertainty was observed during some operating conditions [9]. Non-adaptive controller problems have been overcome by adaptive

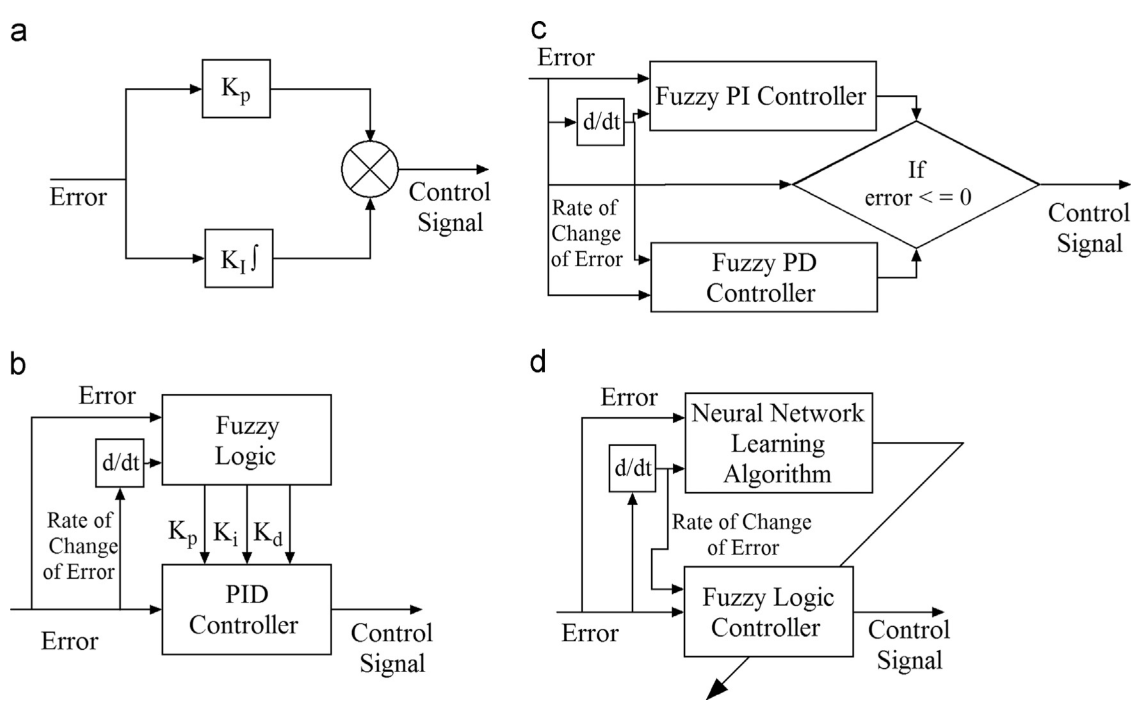

Fig. 1. (a) Proportional Integral controller, (b) Fuzzy Tuned PID controller, (c) Fuzzy Variable Structure controller, and (d) proposed ANFIS controller.

controller, i.e., Fuzzy Variable Structure controller and it is shown in Fig. 1(c). The controller has two structures namely, fuzzy proportional derivative and fuzzy Proportional Integral controller. In this controller also, design is based on trial and error method and it required more number of rules, i.e., totally 98 rules. Performance uncertainty was noticed during set speed variations [11]. In order to overcome all the above notified problems, ANFIS based speed controller has been proposed for brushless DC motor and it is shown in Fig. 1(d). The proposed controller easily overcomes the uncertainty problem arising due to load variations and speed variations with minimum number of rules.

From the literature review, in the area of speed control of BLDC motor, more significance has been given to the design of artificial intelligence based controllers and little attention has been paid to control system performance of the system. Apparently no literature has so far discussed the BLDC controller performance subject to simultaneous step load change and step speed change in all possible conditions. In view of this, the main objectives of the proposed work presented in this paper are the following:

(a) To present an efficient and broad approach for designing ANFIS based controller.
(b) To consider step load change and step speed change simultaneously in all possible conditions, and then obtaining system dynamic responses with ANFIS controller at different load and speed conditions.
(c) To compare the ANFIS controller results with already published results of Proportional Integral controller, Fuzzy Tuned PID controller and Fuzzy Variable Structure controller. Also, to analyze the dynamic performance of the proposed controller with the above control strategy.

In this paper, for the proposed ANFIS based BLDC speed controller, the initial input–output membership functions and 49 rules are constructed by the Fuzzy Inference System (FIS). The modified reference signals, i.e., error, rate of change of error and control signal from Fuzzy Tuned PID controller is used in off-line for updating the parameters of ANFIS as per the proposed methodology. ANFIS tool box in MATLAB environment has been used to design the proposed Adaptive Neuro-Fuzzy System (ANFIS) controller and integrated with simulink tool box for performing simulation analysis. The performance of the proposed ANFIS controller is analyzed and compared with classical Proportional Integral controller [3], Fuzzy Tuned PID controller [9] and Fuzzy Variable Structure controller [11]. Simulation results have been presented to validate the effectiveness of the proposed controller under varying load and set speed conditions.

3. Mathematical model of the BLDC motor drive

The BLDC motor mathematical model can be represented by the following equation in matrix form:

$$\begin{bmatrix} L_a & M_{ab} & M_{ac} \\ M_{ba} & L_b & M_{bc} \\ M_{ca} & M_{cb} & L_c \end{bmatrix} \frac{d}{dt} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} = \begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} - \begin{bmatrix} R_a & 0 & 0 \\ 0 & R_b & 0 \\ 0 & 0 & R_c \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} - \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix} \tag{1}$$

where V_a, V_b and V_c denote phase voltages of the motor. R_a, R_b and R_c represent stator winding resistances. Phase currents of the motor are represented by i_a, i_b and i_c. Self inductances of the motor winding are represented by L_a, L_b and L_c and the mutual inductances between stator windings are denoted by M_{ab}, M_{ac}, M_{ba}, M_{bc}, M_{ca} and M_{cb}.

The electromechanical torque is expressed as

$$T_{em} = J\frac{d\omega_r}{dt} + B\omega_r + T_L \tag{2}$$

where J, B and ω_r denote the moment of inertia, frictional coefficient and angular velocity of the motor, respectively. T_L is the load torque.

Since the electromagnetic torque of 3-phase BLDC motor is dependent on the current, speed and back-EMF waveforms [21,22], the equation for instantaneous electromagnetic torque can be modified and represented as

$$T_{em} = \frac{1}{\omega_m}(e_a i_a + e_b i_b + e_c i_c) \tag{3}$$

4. 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., layer 1 to layer 5. The proposed ANFIS controller structure consists of four important blocks that are fuzzification, knowledge base, neural network and the Defuzzification. 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 layer 4 and transforms the fuzzy classification results into a crisp value [14]. ANFIS modeled 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 ANFIS controller for controlling the speed of BLDC motor.

4.1. ANFIS control scheme for speed control of BLDC motor

The development of the control strategy for speed control of the BLDC motor with proposed ANFIS controller is presented in Fig. 2.

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 BLDC motor by controlling

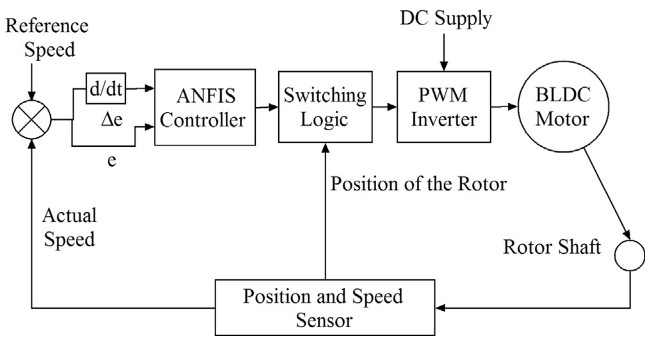

Fig. 2. Proposed ANFIS controller for BLDC motor.

the dc bus voltage through PWM inverter. Based upon error and rate of change of error, 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 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 the following equation:

$$\begin{aligned}
&\text{Rule } 1: \text{ IF } e \text{ is } A_1;\ \Delta e \text{ is } B_1;\text{ then } f_1 = P_1^* e + R_1^*\ \Delta e + s_1\\
&\text{Rule } 2: \text{ IF } e \text{ is } A_1;\ \Delta e \text{ is } B_2;\text{ then } f_2 = P_2^* e + R_2^*\ \Delta e + s_2\\
&\vdots\\
&\text{Rule } i-1: \text{ IF } e \text{ is } A_j;\ \Delta e \text{ is } B_{j-1};\text{ then } f_{i-1} = P_{i-1}^* e + R_{i-1}^*\ \Delta e + s_{i-1}\\
&\text{Rule } i: \text{ IF } e \text{ is } A_j;\ \Delta e \text{ is } B_j;\text{ then } f_i = P_i^* e + R_i^*\ \Delta e + s_i
\end{aligned} \tag{4}$$

where

$$e = \omega_{ref} - \omega_r \tag{5}$$

$$\Delta e = \frac{d(\omega_{ref} - \omega_r)}{dt} \tag{6}$$

$$f_i = P_i e + R_i\ \Delta e + s_i \tag{7}$$

where ω_{ref} is the reference speed, ω_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 Δe. q is the number of membership functions for the fuzzy systems of inputs e and Δe. f_i is the linear consequent functions defined in terms of inputs e and Δe. 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 Fig. 3.

The error and rate of change of error, i.e., e and Δe as mentioned in Eqs. (5) and (6) are given as input to layer 1. In layer 1, every node is an adaptive node with a particular fuzzy membership function specifying the degrees of the inputs which satisfies the quantifier. The following equation represents the node outputs for the two inputs:

$$\begin{aligned}
L_{1,j} &= \mu A_j(e) \quad \text{for } j = 1, 2, \ldots, q\\
L_{1,j} &= \mu B_j(\Delta e) \quad \text{for } j = 1, 2, \ldots, q
\end{aligned} \tag{8}$$

The membership functions considered for A and B in Eq. (8) are triangular-shaped functions and their representations are given in

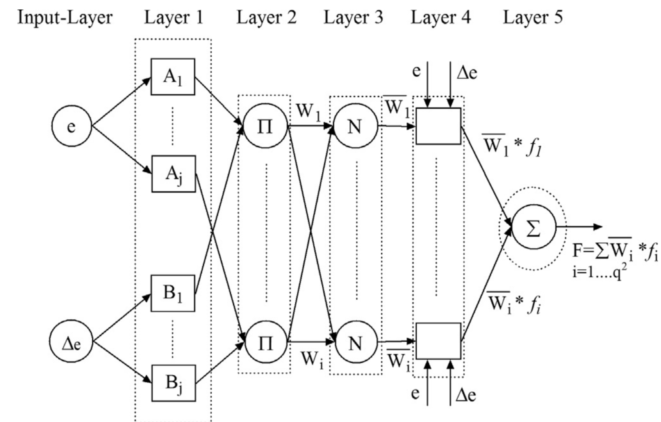

Fig. 3. Structure of a five-layer ANFIS.

the following equations:

$$\mu A_j(e, a_j, b_j, c_j) = \begin{cases} 0, & e \le 0\\ \frac{e - a_j}{b_j - a_j}, & a_j \le e \le b_j\\ \frac{c_j - e}{c_j - b_j}, & b_j \le e \le c_j\\ 0, & c_j \le e \end{cases} \tag{9}$$

$$\mu B_j(\Delta e, x_j, y_j, z_j) = \begin{cases} 0, & \Delta e \le 0\\ \frac{\Delta e - x_j}{y_j - x_j}, & x_j \le \Delta e \le y_j\\ \frac{z_j - \Delta e}{z_j - y_j}, & y_j \le \Delta e \le z_j\\ 0, & z_j \le \Delta e \end{cases} \tag{10}$$

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 layer 2, every node is a fixed node labeled π. $L_{2,i}$ output is the product of all incoming signals and it is given in the following equation:

$$L_{2,i} = W_i = \begin{bmatrix} W_1 & \cdots & W_q\\ \vdots & \ddots & \vdots\\ W_{q^2-(q-1)} & \cdots & W_{q^2} \end{bmatrix} = \begin{bmatrix} \mu A_1 \times \mu B_1 & \cdots & \mu A_1 \times \mu B_q\\ \vdots & \ddots & \vdots\\ \mu A_q \times \mu B_1 & \cdots & \mu A_q \times \mu B_q \end{bmatrix} \tag{11}$$

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)$=A \times B$) is used to obtain the firing strength (W_i). In layer 3, every node is a fixed node labeled N. The output of the ith node is the ratio of the firing strength of the ith rule (W_i) to the sum of the firing strength of all the rules and is given in the following equation:

$$L_{3,i} = \overline{W_i} = \frac{W_i}{\sum_{1=1}^{q^2} W_i} \tag{12}$$

This output gives a normalized firing strength. In layer 4, every node is an adaptive node with a node function given by the following equation:

$$L_{4,i} = \overline{W_i} f_i = \overline{W_i}(P_i e + R_i\ \Delta e + s_i) \tag{13}$$

where $\overline{W_i}$ 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 layer 5, the single node is a fixed node labeled Σ. It computes the overall output as the summation of all incoming signals and it is given in the following equation:

$$L_{5,1} = \sum_i \overline{W_i} f_i = \frac{\sum_i W_i f_i}{\sum_i W_i} \quad (14)$$

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 and subtractive clustering are employed.

In this paper, 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 [14]. 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 tool box. From the training, a fuzzy inference system with adjusted membership functions has been obtained.

4.2. *Development of simulink model and training of ANFIS controller using MATLAB*

Simulink model for the control of BLDC motor drive has been developed in MATLAB environment using the appropriate tool boxes. Fig. 4 shows the simulink model of the proposed controller.

The simulink model consists of DC supply, PWM inverter, motor measurement system, ANFIS controller, switching logic circuit and BLDC motor. The DC supply input is given to PWM inverter and output of the inverter is fed to the BLDC 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 ANFIS speed controller. Based upon the inputs, ANFIS controller generates control signal for the switching logic circuit.

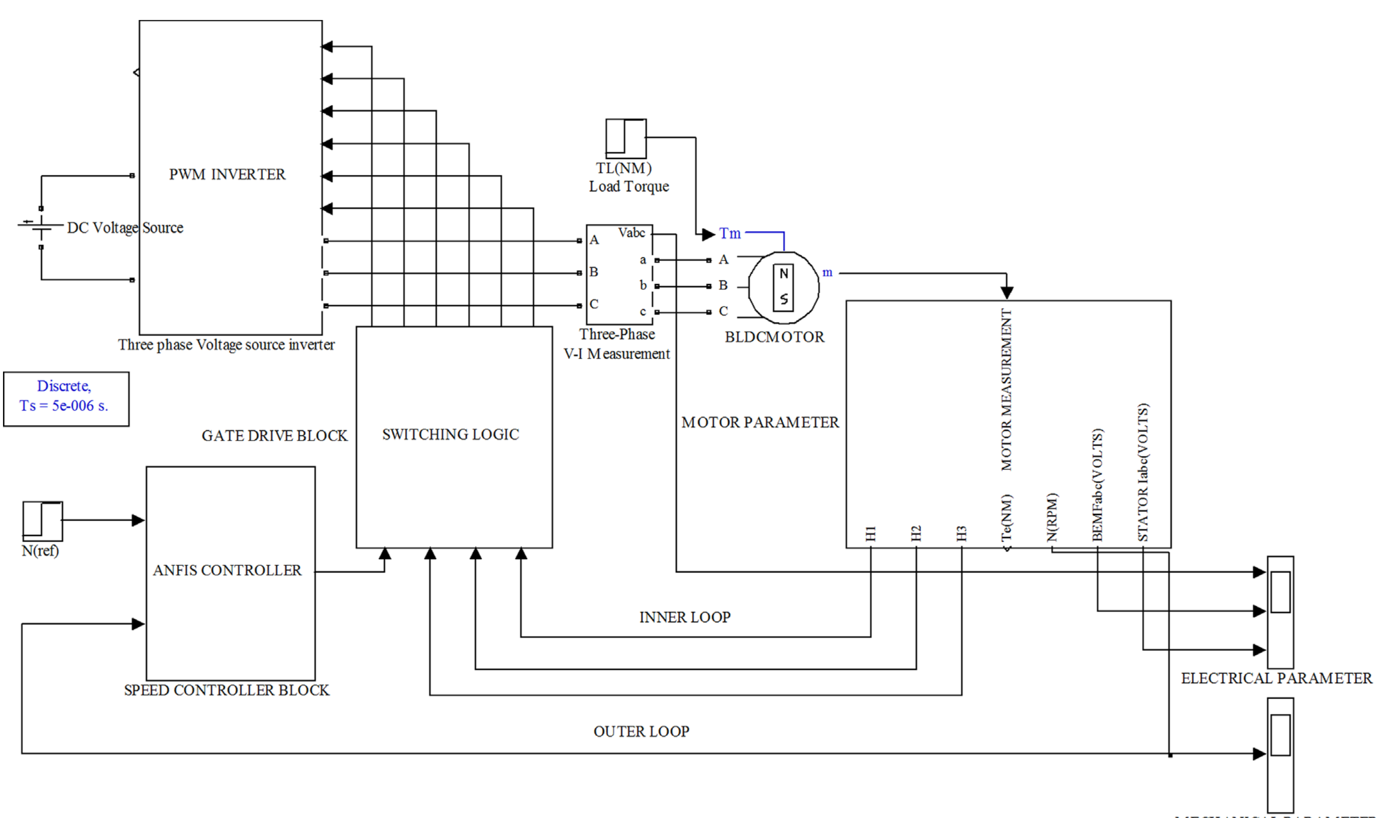

Fig. 4. Simulink model of proposed ANFIS controller for BLDC motor.

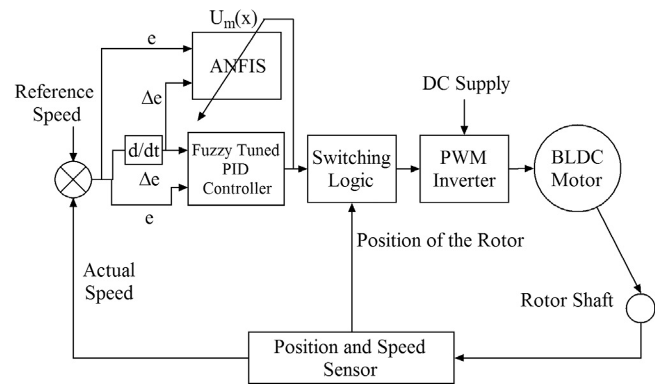

Fig. 5. Block diagram for identifier.

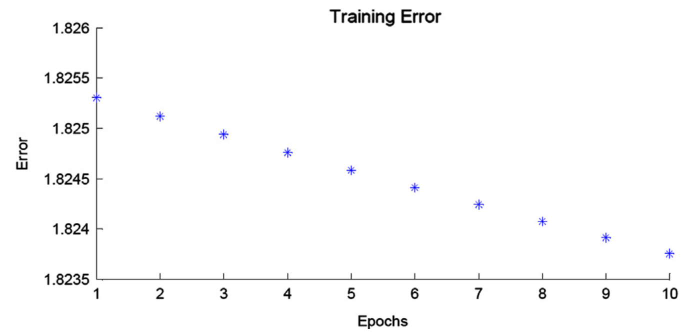

Fig. 8. Training error plot.

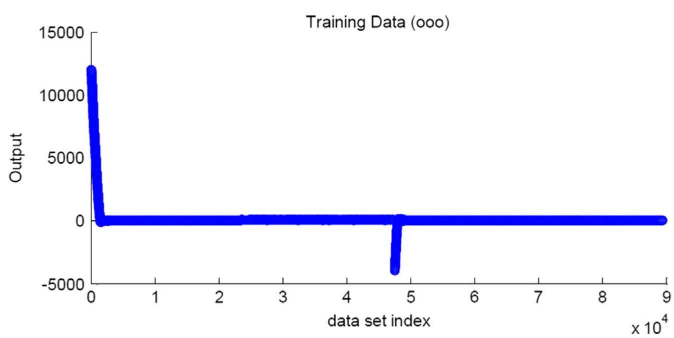

Fig. 6. Modified training data for ANFIS controller.

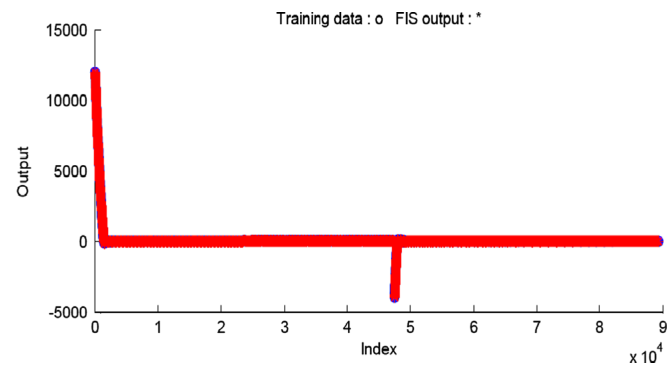

Fig. 9. Testing of trained data with test data.

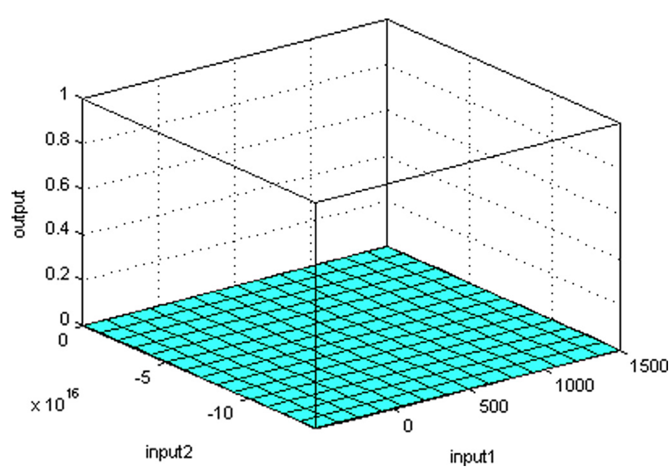

Fig. 7. Initial rule base for T–S fuzzy inference system.

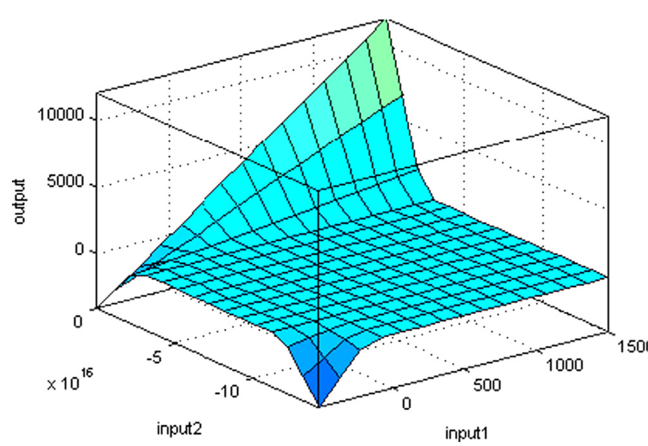

Fig. 10. Final rule base for T–S fuzzy inference system.

Table 1
Initial input membership function.

Distribution of membership function	A_j or e			B_j or Δe		
	a_j	b_j	c_j	x_j	y_j	z_j
1	−830	−497.1	164.3	-1.642×10^{17}	-1.407×10^{17}	-1.173×10^{17}
2	−497.1	−164.3	168.5	-1.407×10^{17}	-1.173×10^{17}	-9.382×10^{16}
3	−164.3	168.6	501.4	-1.173×10^{17}	-9.382×10^{16}	-7.037×10^{16}
4	168.6	501.4	834.3	-9.382×10^{16}	-7.037×10^{16}	-4.691×10^{16}
5	501.4	834.3	1167	-7.037×10^{16}	-4.691×10^{16}	-2.346×10^{16}
6	834.3	1167	1500	-4.691×10^{16}	-2.346×10^{16}	5.066×10^{4}
7	1167	1500	1833	-2.346×10^{16}	5.066×10^{4}	2.346×10^{16}

The switching logic circuit generates gating signals based upon the rotor position and control signal received from the 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 BLDC 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. Fig. 5 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 ANFIS controller is modeled 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 ANFIS based identifier are the input error signal e and rate of change of error Δe of the BLDC motor. The problem is to find the proper parameter values for the ANFIS structure and control signal for the switching logic circuit to minimize identifier output error for all input values of e and Δe.

The period of identifier reference signal is 9×10^4 samples and the mathematical expression for the identifier reference signal is given in Eq. (15). Using Eqs. (16) and (17), the identifier reference signal is modified to obtain desired output signal. Fig. 6 shows the modified training data for the ANFIS controller:

$$U(x)=\begin{cases}\frac{(1.2\times10^4)\times(1550-x)}{1540}, & \text{if } 0<x\le1540\\ 10, & \text{if } 1540<x\le23,400\\ 50, & \text{if } 23,400<x\le47,500\\ \frac{(6\times10^4)\times(x-47,795)}{47,795}, & \text{if } 47,500<x\le48,000\\ 25, & 48,000<x\le90,000\end{cases} \tag{15}$$

$$m(x)=\begin{cases}-x\times\frac{10}{47,500}, & \text{if } 0<x\le47,500\\ x\times\frac{10}{47,500}, & \text{if } 47,500<x\le90,000\end{cases} \tag{16}$$

$$U_m(x)=\begin{cases}\frac{(1.2\times10^4)\times(1550-x+m(x))}{1540}, & \text{if } 0<x\le1540\\ 10+m(x), & \text{if } 1540<x\le23,400\\ 50+m(x) & \text{if } 23,400<x\le47,500\\ \frac{(4\times10^4)\times(x-47,795+m(x))}{47,795}, & \text{if } 47,500<x\le48,000\\ 25+m(x) & \text{if } 48,000<x\le90,000\end{cases} \tag{17}$$

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 PID controller to train the 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 Fig. 7 and initial input membership function is provided in Table 1.

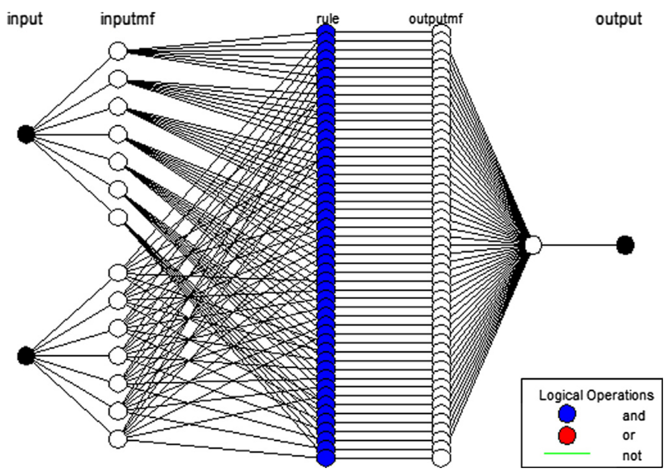

Fig. 11. Proposed ANFIS model structure for BLDC motor.

Table 2
Specifications of BLDC motor drive.

Specifications	Value
Rated voltage (V)	470
Rated current (A)	50
Rated speed (rpm)	1500
Stator phase resistance R (Ω)	3
Stator phase inductance L (H)	0.001
Flux linkage established by magnets (V s)	0.175
Voltage constant (V/rpm)	0.1466
Torque constant (N m/A)	1.4
Moment of inertia (kg m^2/rad)	0.0008
Friction factor (N m/(rad/s))	0.001
Pole pairs	4

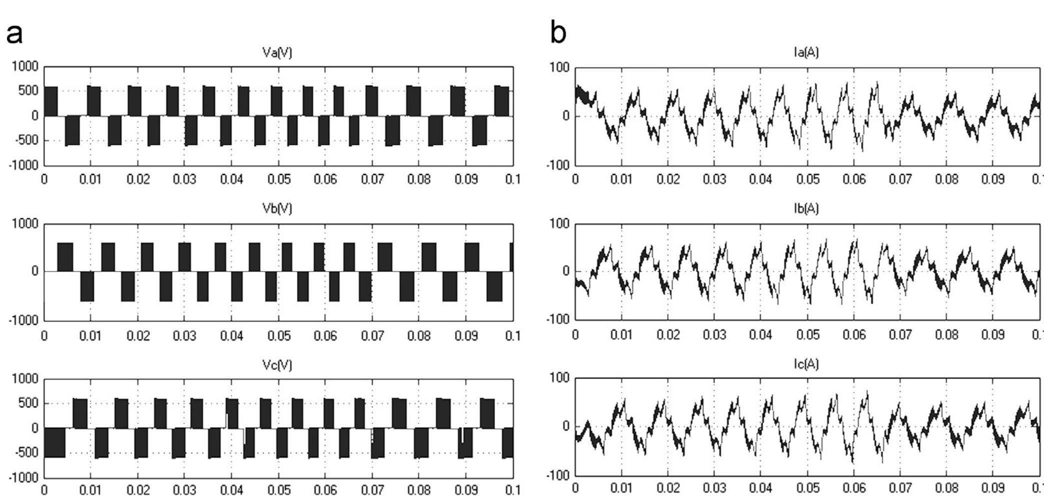

Fig. 12. (a) Phase voltage waveforms based on the rotor position at 1500 rpm and (b) phase current waveforms based on the rotor position at 1500 rpm.

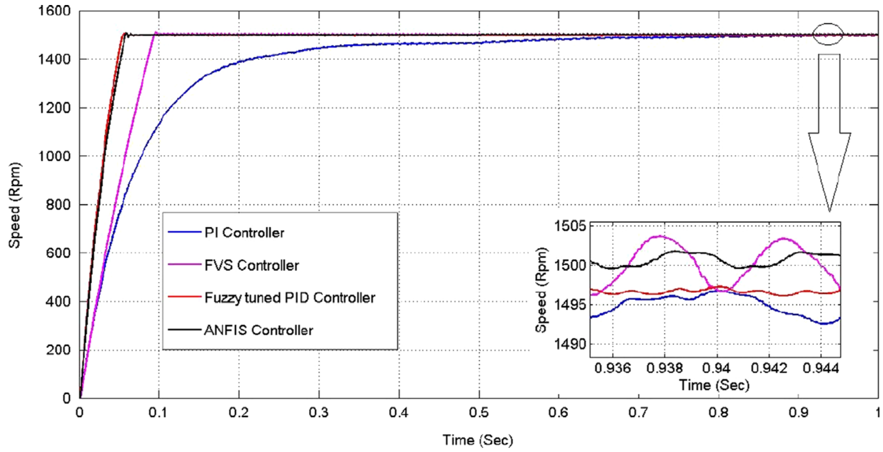

Fig. 13. Speed response of BLDC motor for four controllers.

Table 3
Comparison of response parameters for constant load condition.

Controller	Rise time (s)	Peak value (rpm)	% peak over shot	Peak time (s)	Settling time (s)	Steady state error (rpm)	% steady state error
PI	0.255	–			1	8	0.54
FVS	0.092	1510.5	0.7	0.0923	0.1	3.5	0.24
Fuzzy Tuned PID	0.048	1506	0.4	0.0541	0.064	3	0.2
ANFIS	0.05	1511	0.73	0.0528	0.0611	1.5	0.1

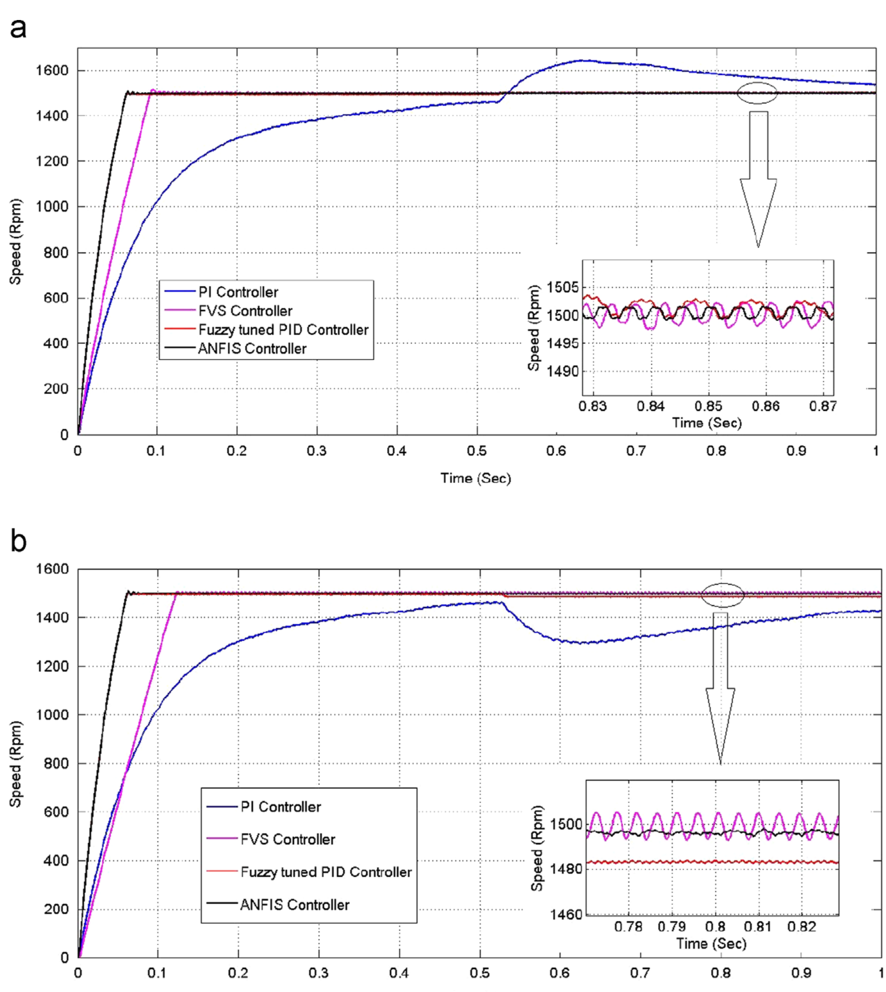

Fig. 14. (a). Comparison of controllers performance for load change from 25 N m to 15 N m and (b) comparison of controllers performance for load change from 25 N m to 35 N m.

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. Ten epochs have been considered for training and Fig. 8 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. Fig. 9 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 Fig. 10.

Fig. 11 shows the proposed ANFIS model structure. The structure consists of five layers. 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.

Table 4
Comparison of response parameters for varying load conditions.

Parameters	Load conditions	PI controller	FVS controller	Fuzzy Tuned PID	ANFIS
% peak overshoot	Case A	9.5	0.17	0.24	0.13
% peak undershoot	Case B	14	0.54	1.13	0.33
Steady state error (rpm)	Case A Case B	8 20	3.5 6	2.5 18	2 3
Recovery time (s)	Case A Case B	1.8 2	0 0	0.52 0.65	0 0

5. Simulation results and discussion

To validate the proposed control strategies described above, simulation has been carried out for the BLDC motor drive system using MATLAB/SIMULINK. The specifications used for the BLDC motor drive system is given in the following Table 2.

Fig. 12(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°. Fig. 12(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 A for all I_a, I_b and I_c.

5.1. Response of the motor for constant load condition

Simulation results of speed response of BLDC motor using Fuzzy Variable Structure, Fuzzy Tuned PID, classical PI controller and proposed ANFIS controllers are shown in Fig. 13. The simulation

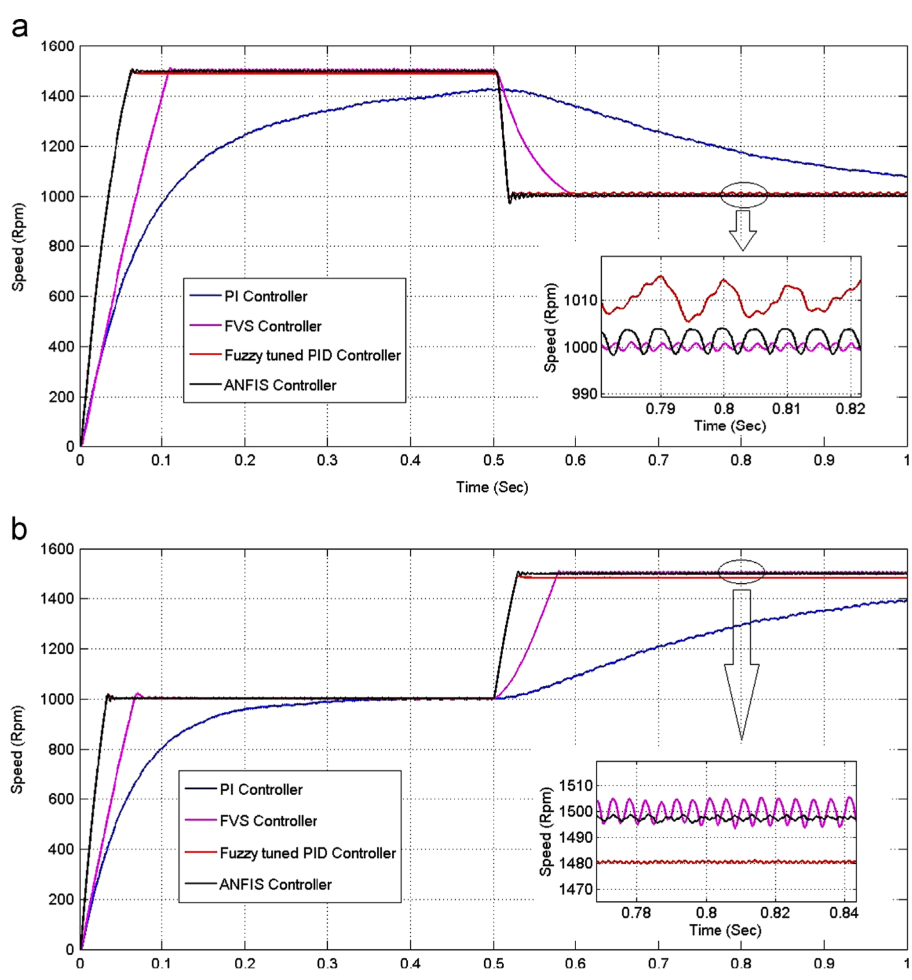

Fig. 15. (a). Comparison of controllers performance – speed change from 1500 rpm to 1000 rpm and (b) comparison of controllers performance – speed change from 1000 rpm to 1500 rpm.

Table 5
Comparison of response parameters for change in set speed conditions.

Parameters	Speed conditions	PI controller	FVS controller	Fuzzy Tuned PID	ANFIS
Steady state error (rpm)	Case A	10	2.5	10	2
	Case B	20	5	20	3
Recovery time (s)	Case A	1.8	0.61	0.53	0.52
	Case B	1.9	0.6	0.55	0.54

result has been obtained by keeping the reference speed at 1500 rpm and the load torque constant at 25 N m. From the response plots shown below, for the PI controller, the drive attains the set or reference speed in 1 s. If the Fuzzy Variable Structure controller is used, reference speed is reached in 0.1 s and it is only 0.064 s for Fuzzy Tuned PID controller and 0.0611 s for 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 3.

From the results shown above, all the vital performance indexes are in favor of ANFIS controller only. With the newly developed controller, the BLDC drive system will have superior rise time, steady state error and settling time characteristics.

5.2. 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 proposed ANFIS controller, simulation results has been obtained for varying load conditions also. First, the load torque is decreased from 25 N m to 15 N m and then it is increased from 25 N m to 35 N m. Fig. 14(a) and (b) 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. 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 N m to 15 N m and Case B represents increase in load torque from 25 N m to 35 N m.

From the results, it is clear that, the proposed ANFIS controller for the BLDC motor drive is superior in all aspects when compared with other controllers. When the load is increased or decreased, the proposed 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.

5.3. 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. 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 Fig. 15(a) and (b).

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 5.

Steady state error and recovery time measured are in favor of ANFIS controller only. The proposed ANFIS controller for BLDC motor drive is performing very well under change in reference speed conditions also when compared with other controllers.

6. Conclusion

An efficient controller has been proposed for the brushless DC motor drive. The proposed controller, i.e., ANFIS controller has been compared with other controllers under varying load and set speed conditions. Various control system parameters such as overshoot, undershoot, steady state error, rise time, settling time and recovery time for all controllers considered has been measured, analyzed and compared. The results reveal that the ANFIS controller outperforms other controllers in all aspects. Since simulation has been performed and analyzed for varying speed and load conditions, this proposed controller for BLDC drive can be readily implemented for real time applications.

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