



ELECTRICAL ENGINEERING

Design adaptive neuro-fuzzy speed controller for an electro-mechanical system

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Abstract In this paper an adaptive neuro-fuzzy inference system (ANFIS) controller using error and derivative of error inputs is proposed for the speed control of a separately excited DC motor (SEDM) using chopper circuit. This paper investigates the design and simulation of an adaptive neuro-fuzzy inference system (ANFIS) controller for the speed of DC motor. The performance of the proposed system has been compared with conventional one, where the conventional PI controller (speed controller) in the chopper-fed DC motor drive is replaced by the adaptive neuro-fuzzy controller to improve the dynamic behavior of the model. Computer Simulation is conducted to demonstrate the performance of the proposed controller and results show that the proposed design succeeded over the conventional PI controller where it make reduction of number of ripples and rise time. The entire system has been modeled using MATLAB 2009 toolbox.

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1. Introduction

Direct current (DC) motors have been widely used in many industrial applications such as electric vehicles, steel rolling mills, electric cranes, and robotic manipulators due to precise,

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wide, simple, and continuous control characteristics. So we studied this example of its importance and try to solve its problems in different ways. Traditionally armature control method was widely used for the speed control of low power DC motors. However the controllability, cheapness, higher efficiency, and higher current carrying capabilities of static power converters brought a major change in the performance of electrical drives. The desired torque-speed characteristics could be achieved by the use of conventional proportional integral-derivative (PID) controllers. Since PID controllers require exact mathematical model. The adaptive neuro-fuzzy inference system (ANFIS), developed in the early 1990s by Jang [1], combines the concepts of fuzzy logic and neural networks to form a hybrid intelligent system that enhances the ability to automatically learn and adapt hybrid systems have been used by researchers for modeling and predictions in various engineering systems. The basic idea behind these

neuro-adaptive learning techniques is to provide a method for the fuzzy modeling procedure to learn information about a data.

Set, in order to automatically compute the membership function parameters that best allow the associated FIS to track the given input/output data. The membership function parameters are tuned using a combination of least squares estimation and back-propagation algorithm. These parameters associated with the membership functions will change through the learning process similar to that of a neural network. Their adjustment is facilitated by a gradient vector, which provides a measure of how well the FIS is modeling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of several optimization routines could be applied in order to adjust the output so as to reduce error between the actual and desired outputs. This allows the fuzzy system to learn from the data it is modeling. The approach has the advantage over the pure fuzzy paradigm that the need for the human operator to tune the system by adjusting the bounds of the membership functions is removed. An open loop control system which can predict the dynamic behavior of systems involving mechanic and electronic modules has been successfully designed and implemented to control the speed of a DC motor [2]. The superior performance of artificial intelligence (AI) based controllers urged power system and power electronic engineers to replace conventional speed control circuit with intelligent speed controllers [3,4].

2. Modeling of DC motor

The DC motor is the obvious proving ground for advanced control algorithms in electric drives due to the stable and straight forward characteristics associated with it. It is also ideally suited for trajectory control applications. From a control systems point of view, the DC motor can be considered as SISO plant, there by eliminating the complications associated with a multi-input drive system [5].

2.1. Dynamics of a DC motor

Dynamics of a DC motor is described by the following equation:

$$K_p \omega(t) = -Ri(t) - L \frac{di(t)}{dt} + V(t) \tag{1}$$

$$K_i i(t) = J \frac{d\omega(t)}{dt} + D\omega(t) + T_1(t) - T_f \tag{2}$$

where the parameters of the DC motor are shown in Table 1. In order to control a plant, a discrete time model of the plant is required. The following discrete time model of a DC motor is used:

$$V(K) = A_1 \omega(K+1) + A_2 \omega(K) + A_3 \omega(K-1) + A_4(K, K-1) \tag{3}$$

where k indicates the k th discrete time moment, $A_1, A_2,$ and A_3 are real constants, and A_4 is a real parameter which depends on the load of the motor [3].

2.2. Chopper-fed DC motor drive

A DC motor consists of stator and armature winding in the rotor as in Fig. 1. The armature winding is supplied with a DC voltage that causes a DC current to flow in the winding.

The field circuit of the motor is excited by a constant source. The steady state speed of the motor can be described as:

$$\omega = \frac{V - iR}{K_1} \tag{4}$$

where k_1 is the duty cycle. The speed of a DC motor can be controlled by varying the voltage applied to the terminal. These can be done by using a pulse-width modulation (PWM) technique as shown in Fig. 2, where T is the signal period, td is the pulse-width, and V_m is the signal amplitude. A

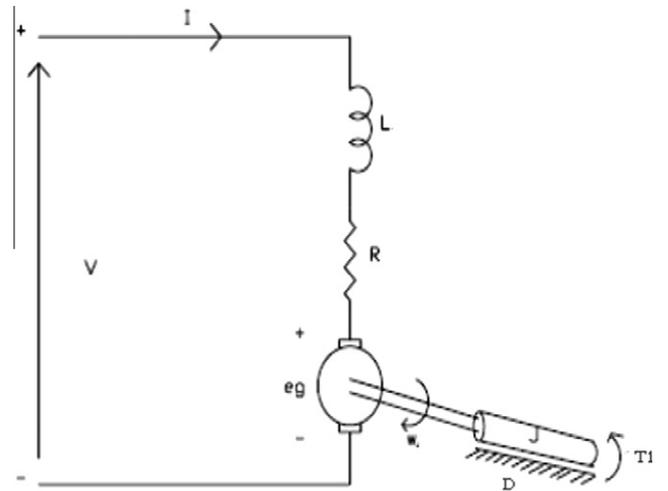


Figure 1 Dynamic equivalent circuits of a DC motor.

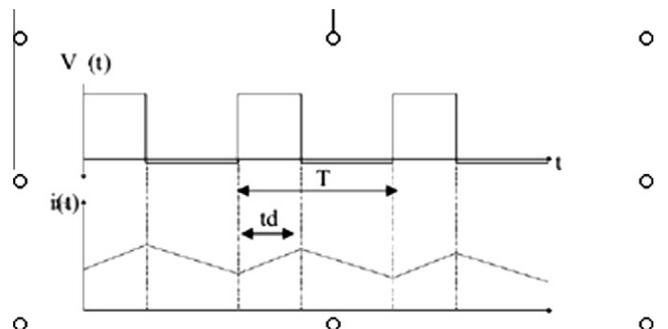


Figure 2 Pulse width modulation.

Table 1 Definition of parameters.

No	Definition	Symbols	Unit
1	Rotor speed	$\omega(t)$	rad s^{-1}
2	Armature resistance	R	Ω
3	Armature inductance	L	H
4	Armature current	$i(t)$	A
5	Armature voltage	$V(t)$	v
6	Load torque	T_L	Nm
7	Rotor inertia	J	kg m^2
8	Is torque constant	K_t	V s rad^{-1}
9	Back EMF constant	k_p	V s rad^{-1}
10	Viscous friction coefficient	D	N m s rad^{-1}
11	Coulomb friction torque	T_f	N m

field voltage signal with varying pulse-width is applied to the motor terminal. The average voltage is calculated from

$$V_{ag} = \frac{1}{T} \int_0^T V(t) dt = \frac{t_d}{T} V_m = K_1 V_m \quad (5)$$

It can be mentioned from these equation that the average DC component of the voltage signal is linearly related to the pulse-width of the signal, or the duty cycle of the signal, since the period is fixed.

The PWM voltage waveform for the motor is to be obtained by using a special power electronic circuit called a DC chopper. The action done by the DC chopper is supplying a train of unidirectional voltage pulses to the armature winding of the PM-DC motor as shown in Fig. 2. If t_d is varied keeping T constant, the resultant voltage wave represents a form of pulse width modulation, and hence the chopper is named as the PWM chopper [6,7].

2.3. Modeling and control of SEDM using MATLAB SimPowerSystems

Fig. 3 shows MATLAB/SimPowerSystems model of a separately excited DC motor which has been selected to control [8]. It consists of a separately excited DC motor fed by a DC source through a chopper circuit. A single GTO thyristor with its control circuit and a free-wheeling diode form the chopper circuit. The motor drives a mechanical load characterized by inertia J , friction coefficient B , and load torque T_L . The control circuit consists of a speed control loop and a current control loop. A proportional-integral (PI) speed control loop senses the actual speed of the motor and compares it with the reference speed to determine the reference armature current required by the motor. One may note that any variation in the actual speed is a measure of the armature current required by the motor. The current control loop consists of a hysteresis current controller (HCC). The block diagram of a hysteresis current controller is shown in Fig. 4. HCC is used to generate switching patterns required for the chopper circuit by comparing the actual current being drawn by the motor with the reference current. A

positive pulse is generated if the actual current is less than reference armature current, whereas a negative pulse is produced if the actual current exceeds reference current [9]. In this paper, an adaptive neuro-fuzzy inference system (ANFIS) controller has been proposed for the speed control of separately excited DC motor in the constant torque region, which is detailed in the following part of this paper.

3. Adaptive neuro-fuzzy mode speed controller

3.1. Adaptive neuro-fuzzy principle

A typical architecture of an ANFIS is shown in Fig. 5, in which a circle indicates a fixed node, whereas a square indicates an adaptive node. For simplicity, we consider two inputs x, y and one output z . Among many FIS models, the Sugeno fuzzy model is the most widely applied one for its high interpretability and computational efficiency. For a first order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules can be expressed as:

Rule 1: if x is A_1 and y is B_1 , then

$$z_1 = p_1x + q_1y + r_1 \quad (6)$$

Rule 2: if x is A_2 and y is B_2 , then

$$z_2 = p_2x + q_2y + r_2 \quad (7)$$

where A_i and B_i are the fuzzy sets in the antecedent, and p_i, q_i and r_i are the design parameters that are determined during the training process. As in Fig. 5. The ANFIS consists of five layers [10,11].

The task done by each layer is explained next.

Layer 1: Is composed of a number of computing nodes whose activation functions are fuzzy logic membership functions (triangular functions).

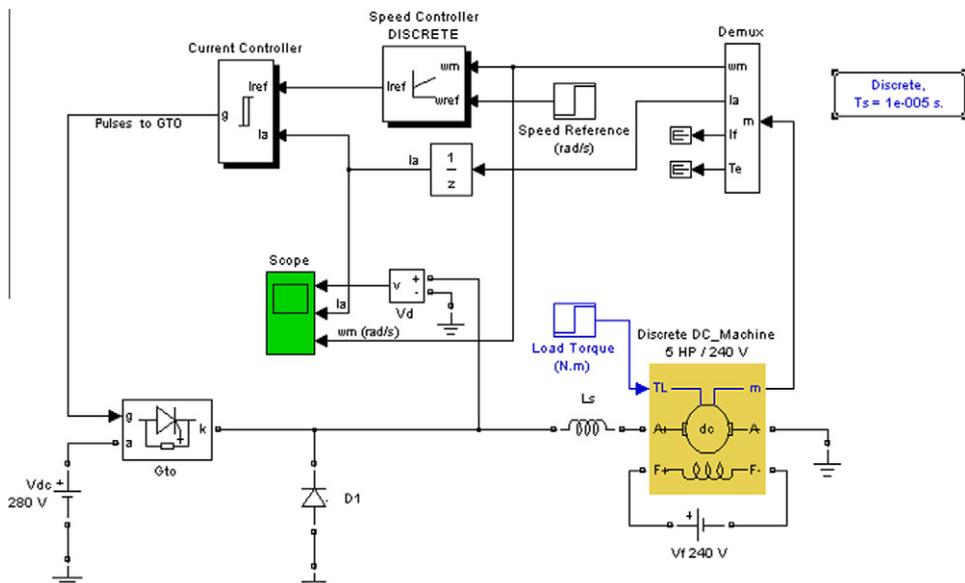


Figure 3 MATLAB/SimPowerSystems model of a separately excited DC motor speed control.

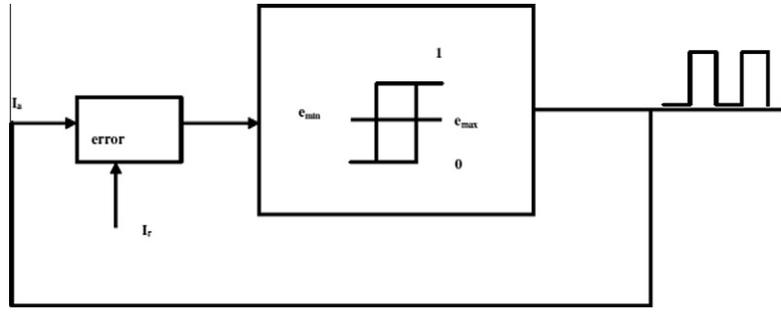


Figure 4 Block diagram of a hysteresis current controller.

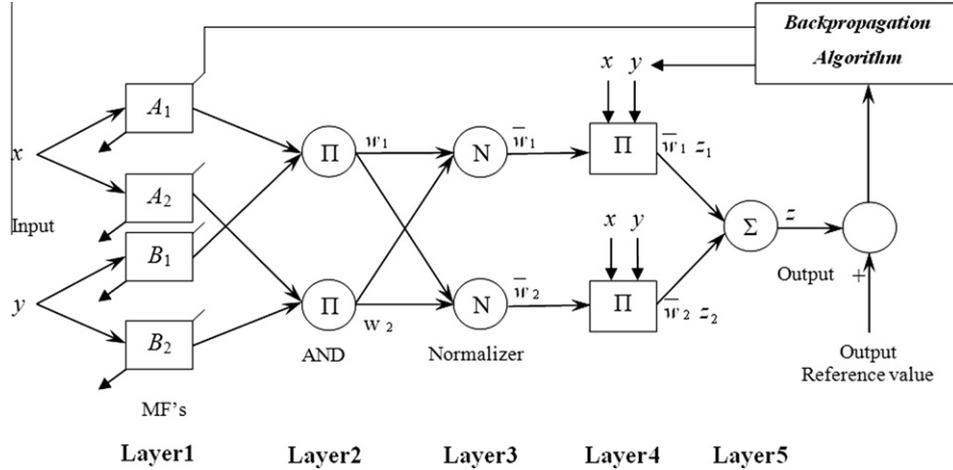


Figure 5 Corresponding ANFIS architecture.

- Layer 2: Chooses the minimum value of the inputs.
- Layer 3: Normalizes each input with respect to the others (The i th node output is the i th input divided by the sum of all the other inputs).
- Layer 4: i th node output is a linear function of the third layer's i th node output and the ANFIS input signals.
- Layer 5: Sums all the incoming signals. The ANFIS structure can be tuned automatically by a least-square estimation (for output membership functions) and a back propagation algorithm (for output and input membership functions) [11].

3.2. Adaptive neuro-fuzzy controller

The ANFIS controller generates change in the reference voltage V_{ref} , based on speed error e and derivate in the speed error Δe defined as:

$$e(t) = \omega_{ref} - \omega \quad (8)$$

$$\Delta e(t) = [d(\omega_{ref} - \omega)]/dt \quad (9)$$

where ω_{ref} and ω are the reference and the actual speeds. In this study first order Sugeno type fuzzy inference is used for ANFIS and the typical fuzzy rule is:

If e is A_i and de is B_i then

$$z = f(e, de)$$

where A_i and B_i are fuzzy sets in the antecedent and $z = f(e, de)$ is a crisp function in the consequent.

The significances of ANFIS structure are:

- Layer 1: Each adaptive node in this layer generates the membership grades for the input vectors A_i , $i = 1, 2, 3$. In this paper, the node function is a triangular membership function:

$$O_i^1 = \mu_{A_i}(e) = \begin{cases} 0 & e \leq a_i \\ \frac{e-a_i}{b_i-a_i} & a_i \leq e \leq b_i \\ \frac{e_i-e}{e_i-b_i} & b_i \leq e \leq c_i \\ 0 & e_i \leq e \end{cases} \quad (11)$$

- Layer 2: The total number of rule is nine in this layer. Each node output represents the activation level of a rule

$$O_i^1 = W_i = \min(\mu_{A_i}(e) \cdot \mu_{B_i}(e)) \quad (12)$$

- Layer 3: Fixed node i in this layer calculates the ratio of the i th rule's activation level to the total of all activation level:

$$O_i^3 = \bar{W}_i = \frac{W_i}{\sum_{j=1}^n W_j} \quad (13)$$

- Layer 4: Adaptive node i in this layer calculates the contribution of i th rule towards the overall output, with the following node function:

$$O_i^4 = \bar{W}_i Z_i = \bar{W}_i (P_i e + q_i de + r_i) \quad (14)$$

Layer 5: The single fixed node in this layer computes the overall output as the sum of each rule's contribution

$$O_i^5 = \sum_{i=1}^2 \bar{W}_i Z_i = \frac{W_1 Z_1 + W_2 Z_2}{W_1 + W_2} \quad (15)$$

The parameters to be trained are a_i , b_i and c_i of the premise parameters and p_i , q_i , and r_i of the consequent parameters.

Fig. 6a and b show optimized membership function for e and Δe after raining (Fig. 7). Shows the ANFIS model structure involved in this work.

The number of epochs was 150 for training. The number of MFs for the input variables e and Δe is 3 and 3 the number of rules is then 9 ($3 * 3 = 9$). The triangular MF is used for two input variables. It is clear from (11) that the triangular MF is specified by two parameters.

Therefore, the ANFIS used here contains a total of 39 fitting parameters, of which 12 ($2 * 3 + 2 * 3 = 12$) are the premise parameters and 27 ($3 * 9 = 27$) are the consequent parameters.

4. Simulation results of speed neuro-fuzzy controller

An adaptive neuro fuzzy inference system (ANFIS) controller is simulated for chopper-fed DC motor drive with parameters

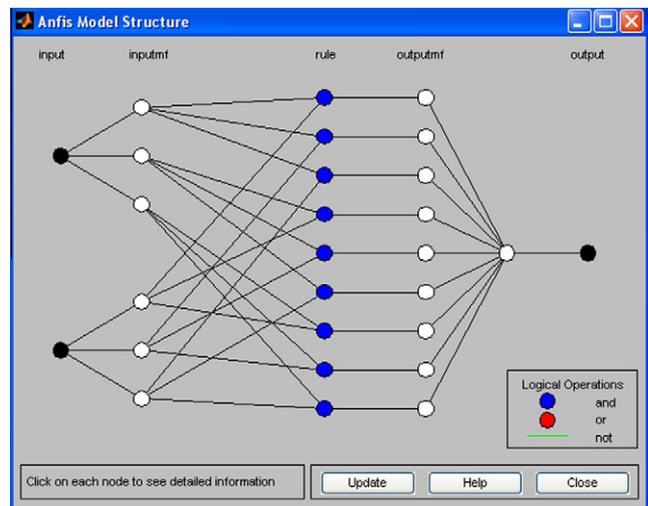


Figure 7 The neuro fuzzy controller structure.

as shown in Table 2. The model chosen here for simulation and is taken from [8], where it is simulated and compared to the conventional PI controller. The second section discusses the comparison between conventional PI controller (speed controller), fuzzy self tuning PID (FPID) controller (where the

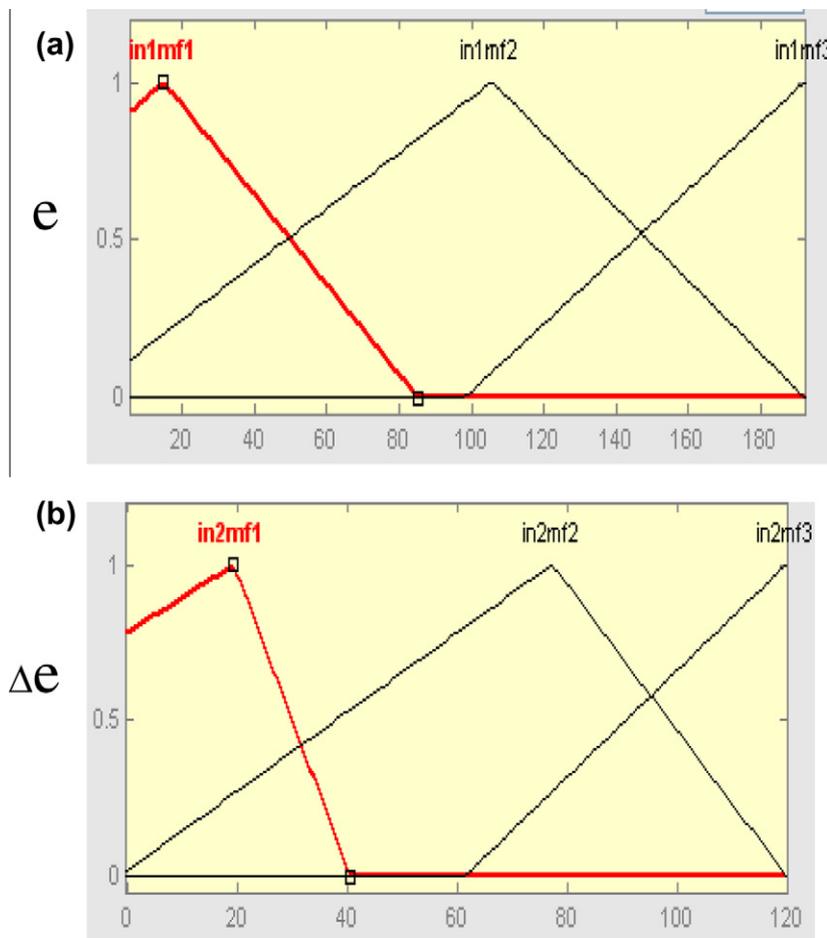


Figure 6 Membership functions for (a) speed error signal and (b) derivative of speed error signal.

Table 2 Definition of parameters and its value.

No	Definition	Symbols	Data/unit
1	Shaft power	P	5 hp
2	Rated Voltage	v	240 (rms)V
3	Armature resistance	R_a	0.6
4	Armature inductance	L_a	0.012 H
5	Field resistance	R_f	240 H
6	Field inductance	L_f	120
7	Moment of inertia	J	0.05 kg m ²
8	Viscous friction coefficient	B	0.2 N m s
9	Coulomb friction torque	T_F	0.5 N m

conventional PI controller (speed controller) in the chopper-fed DC motor drive was replaced by the self tuning PID controller [12] and (ANFIS) controller as shown in Fig. 7. The third and last section discusses the effect of increasing temperature on armature resistance of DC motor [13] and its impact on speed (Fig. 8).

4.1. The following observations can be made after demonstration of chopper-fed DC motor drive

Starting the simulation and observing the motor voltage (V_a), current (I_a) and speed (ω) on the scope.

- (1) $0 < t < 0.8$ s: *Starting and steady state operation:* During this period, the load torque is $T_L = 5$ N m.
- (2) $t = 0.8$ s: *Reference speed Step:* The reference speed is increased from 120 to 160 rad/s. The PI speed controller regulates the speed in approximately 0.25 s while FPID speed controller regulates the speed in ≈ 0.07 s and the ANFIS speed controller regulates the speed in ≈ 0.04 s.

- (3) $t = 1.5$ s: *Load torque step:* When the load torque is suddenly increased from 5 to 25 N m [8] the speed is nearly constant for ANFIS, however for PI and FPID the speed is badly affected.

4.2. Comparisons between the conventional PI, FPID and ANFIS controller

The comparisons between the conventional PI, FPID and ANFIS controller are shown in Figs. 9–11.

Simulation results and comparisons prove that ANFIS performs good response where rise time = 0.08 s, at $t = 0.8$ s (when the reference speed is increased), while for PI speed controller = 0.24 s and for FPID speed controller = 0.2 s.

4.3. Temperature effect on SEDM

In all of the electrical machines, the electrical, magnetic and thermal processes are internally coupled together in some sense. The temperature distribution is affected by the properties of the conducting and magnetic materials and the performance of the electromagnetic force, which is generated from the reaction between stator and rotor. The most temperature sensitive parameters are the winding resistance and the iron core of the stator.

Winding resistance is a major factor in motor selection because it seriously affects K_m . Winding resistance and motor current produce power loss in the form of heat and motor temperature rise (TPR). These losses are also referred to as I^2R losses and directly degrade motor efficiency.

Most motor windings are copper wire which has a positive temperature coefficient. A winding temperature rise from 25 to 155 °C increases wire resistance as much as 50%. Likewise, a proportional decrease in resistance occurs for temperature drops [13].

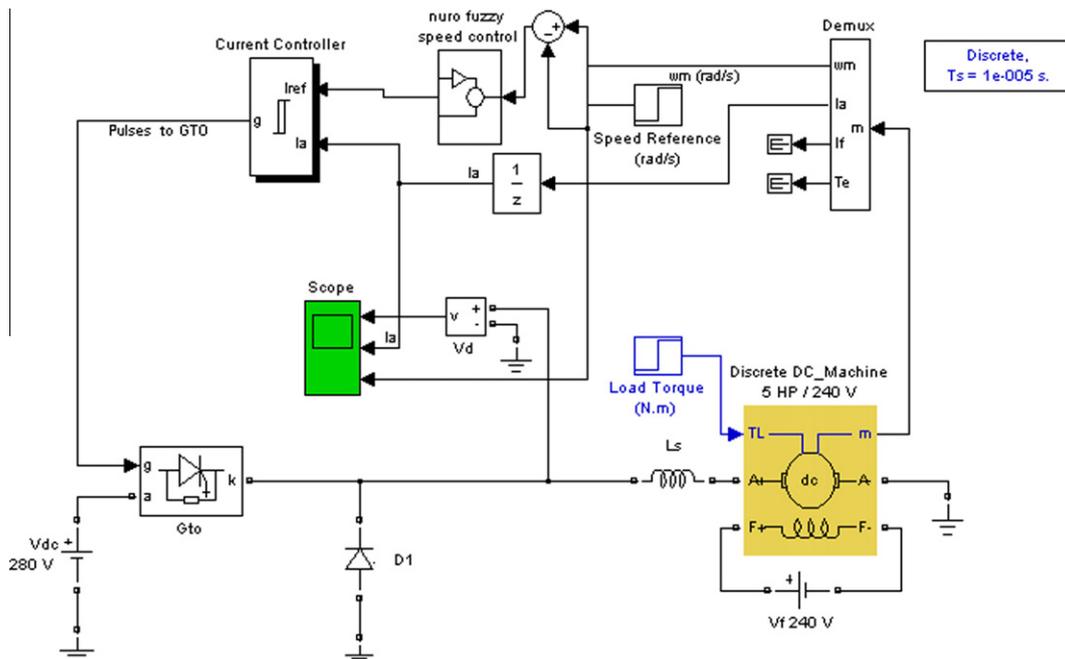


Figure 8 Model of a separately excited DC motor speed control with (ANFIS).

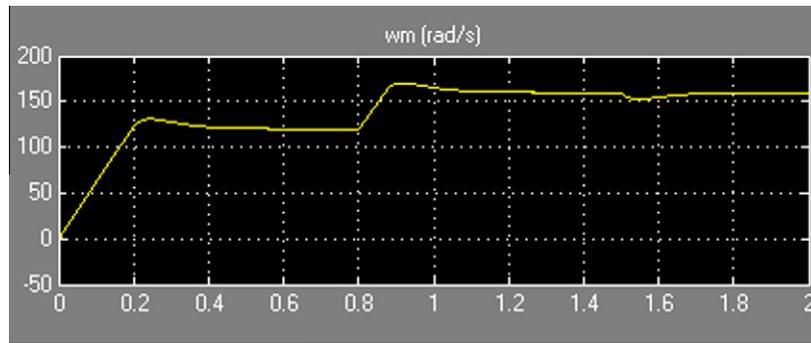


Figure 9 Speed response of pI controller.

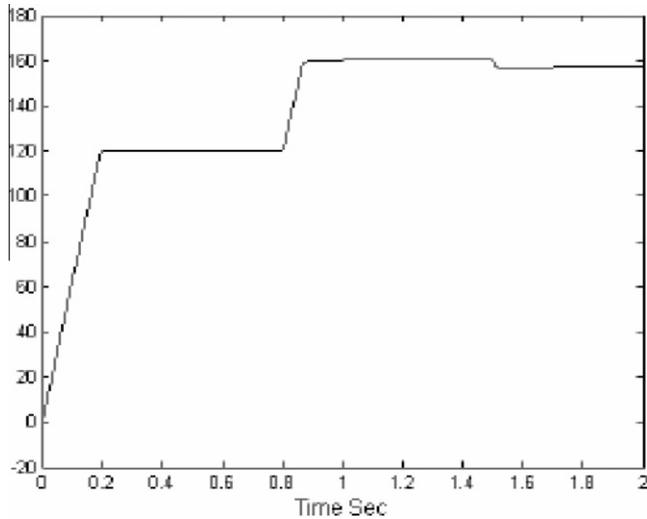


Figure 10 Speed response of (FPID) self tuning controller.

The motor resistance increases with temperature as:

$$R_a(t) = R_a(t_0)[1 + \alpha_0 t] \tag{16}$$

where $R_a(t)$ = resistance at 155 °C, $R_a(t_0)$ = resistance at 25 °C, t = rise in temperature and α_0 = temperature coefficient of resistance at 0 °C = 0.00393 for copper magnet wire. Then $R_a(t) = 0.912 \Omega$.

Figs. 12 and 13 show the effect of increasing temperature on speed of DC motor

- (1) $0 < t < 0.8$ s: *Starting and steady state operation:* During this period, the load torque is $T_L = 5$ N m.
- (2) $t = 0.8$ s: *Reference speed step:* The reference speed is increased from 120 to 160 rad/s. The PI speed controller regulates the speed in approximately 0.3 s while ANFIS speed controller regulates the speed in ≈ 0.1 s.

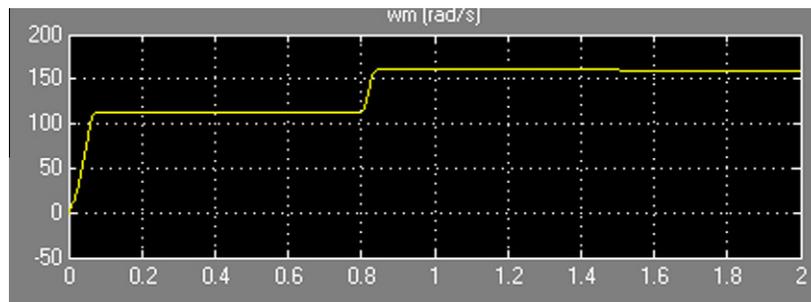


Figure 11 Speed response of (ANFIS).

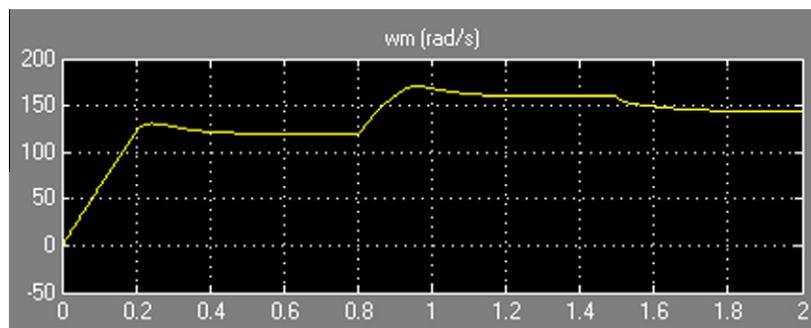


Figure 12 Speed response of pI controller under effect of temperature.

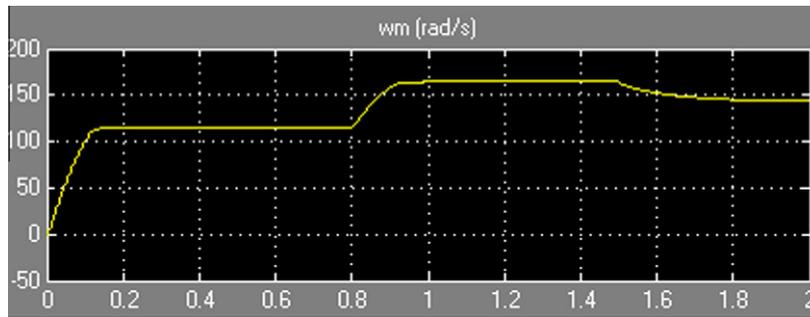


Figure 13 Speed response of (ANFIS) under effect of temperature.

Table 3 Comparison results between PI, FPID, and ANFIS controllers.

Control strategies	Rise time (s)	Time for speed regulation (s)
Conventional PI	0.24	0.25
FPID	0.2	0.07
ANFIS	0.08	0.04

Table 4 Comparison results between PI, FPID, and ANFIS controllers.

Control strategies	Setting time before changing load (s)	Setting time after changing load (s)	Overshoot
Conventional PI	0.58	0.2	Yes
FPID	0.2	0.2	No
ANFIS	0.09	0.02	No

- (3) $t = 1.5$ s: *Load torque step*: When the load torque is suddenly increased from 5 to 25N m [8] the speed is decreased for both PI and ANFIS but in PI controller the speed is badly affected.

5. Conclusions

Speed controller system based on (ANFIS) controller has been successfully developed using MATLAB (2009) to control the speed of a separately excited DC motor. This paper lies in the application of (ANFIS) controller to control a separately excited DC motor. This paper also discusses the effect of increasing temperature on armature resistance of DC motor and its impact on speed. The performance of the system has been compared with conventional PI controller and fuzzy self tuning PID controller. An improved speed response has been achieved with the ANFIS than the other techniques mentioned. The performance has been tested by simulations. There is a reduction in number of ripples as well as steady

state error and rise time and no overshoot appears. Moreover ANFIS controller regulates the speed in time less than previously mentioned controllers and FPID controller as shown in Table 3.

Actually, the proposed ANFIS speed controller improves the performance in both transient and steady state response in comparison to the conventional PI controller as shown in Tables 3 and 4.

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