International Journal of Control and Automation
Vol. 7, No. 12 (2014), pp. 425-436
http://dx.doi.org/10.14257/ijca.2014.7.12.39

Speed Control Based on Adaptive Neuro-Fuzzy Inference System for Permanent Magnet Direct Current Motor

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Abstract

Intelligent control that can be used learning ability and human experiences, is widely used in industrial application such as motors speed control. This paper presents Proportional-Integral-Derivative Controller (PID controller) based on Adaptive Neuro-Fuzzy Inference System (ANFIS) for Permanent Magnet Direct Current (PMDC) motor. ANFIS provides combination of artificial neural network and fuzzy inference systems therefore ANFIS uses advantages of them simultaneously. The proposed PID controller Coefficients are determined by ANFIS. The proposed controller based system is compared with Internal Model Control (IMC) PID controller based system. The Comparison shows that proposed controller improves characteristics in different conditions such as no load, increasing reference speed, applied load and noisy load. Proposed controller based system can improve system performance by smaller fuzzy rule set.

Keywords: *Adaptive Neuro-Fuzzy Inference System, Internal Model Control, PID controller, PMDC motor, Speed control*

1. Introduction

In recent years, PMDC motors are applied in different applications such as robotics and factory automation, industrial equipment and etc. PMDC motors are beneficial in a range of applications, from battery powered devices like power tools, to conveyors and door open ers and pumping equipment.

The PMDC motors become more popular in many control systems because of its high power density, large torque to inertia ratio, small and high efficiency [1].

These motors are done mainly controls through the control of the armature. There are three general methods for controlling motors [1-2]:

- The classic PID controller
- Modern controller
- Intelligent controller

ISSN: 2005-4297 IJCA

Recently, fuzzy inference system (FIS) is widely used because of its good performance, especially in cases when the system or process is complicated and classical approaches don't fulfill the tasks. Additionally, fuzzy system formulates human knowledge in systematic manner and puts them into engineering systems. But there is a problem associated with FIS, which is the time consuming process to tune the parameters of FIS relying on human knowledge by trial and error. So, there has been recently a surge of interest to combine neural network and FIS because of its both advantages of fuzzy inference systems and artificial neural networks [3].

ANFIS which is presented in IEEE transaction in 1993 [4], is widely used industrial applications in recent years.

In recent years, ANFIS widely is used in various control methods. The application examples show how ANFIS and PD (Proportional-Derivative) controllers are applied to BLDC motor simultaneously [3] when ANFIS based Model Reference Adaptive System (MRAS) are used in PMSM [5]. Moreover, stepping and induction motors are controlled by ANFIS as reported in [6,7].

ANFIS based PMDC motor speed controller is proposed thatThe coefficients of proposed PID controller are determined by ANFIS. The proposed controller based system is compared with IMC PID controller based system. Comparison shows that motor performances are improved in various conditions. This paper is organized as follows:

PMDC motor structure is explained in Section 2, followed by describtion of ANFIS. Controller is proposed with details in Section 4 when simulation results are investigated in Section 5 and finally, Section 6 expresses summary conclusion.

2. PMDC Motor Structure

Paper's case study is PMDC motor therefore PMDC motor structure should be studied accurately. At first, the equations are written; these describe the structure of PMDC motor [2, 8].

$$\frac{di_A(t)}{dt} = -\frac{R_A}{L_A} i_A(t) - \frac{K_T}{L_A}\omega_M(t) + \frac{1}{L_A}U_T(t) \tag{1}$$

$$\frac{d\omega_M(t)}{dt} = \frac{K_T}{J_M} i_A(t) - \frac{B_M}{J_M}\omega_M(t) - \frac{1}{J_M}T_L(t) \tag{2}$$

$$\frac{d\theta_M(t)}{dt} = \omega_M(t) \tag{3}$$

Where θ_M is angular position, ω_M is rotor speed, i_A is motor current, B_M is viscous friction constant, J_M is inertia of rotor, T_L is load torque, R_A is armature resistance, L_A is armature inductance, K_T is back electromotive force (emf) constant or torque constant and U_T is applied voltage to motor. In PMDC motor, the electromagnetic torque (T_E) and the backemf (u_b) are proportional to motor current and speed motor, respectively. The back electromotive force (K_T) determined by the strength of magnet, reluctance of iron and number of turns of armature winding. The stator magnetic flux remains essentially constant at all levels of armature current, therefore the torque-speed curve of the PMDC motor is linear [2, 8]. The block diagram of PMDC motor is concluded form equations (1), (2) and (3).

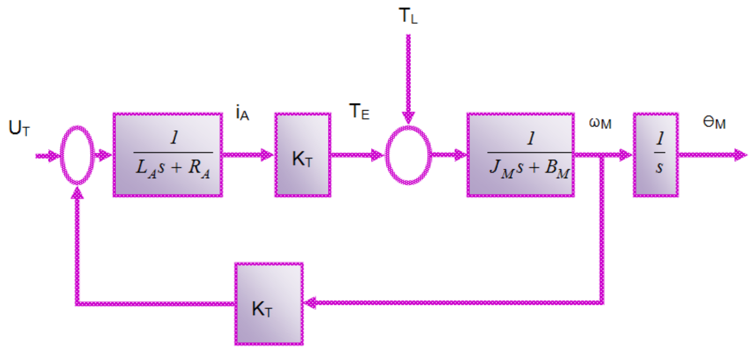


Figure 1. Block diagram of PMDC motor

This block diagram is simulated in Simulink - MATLAB. ANFIS concept is explained in next section.

3. Adaptive Neuro-Fuzzy Inference System

The neuro-fuzzy systems use advantages of neural network and fuzzy systems simultaneously, therefore industrial applications are being progressed in recent years. Moreover, ANFIS overcomes the disadvantages of neural network and fuzzy systems. One of popular neuro-fuzzy methods is called *Adaptive Neuro-Fuzzy Inference System* which is introduced by *Jyh - Shing Roger Jang* [4].

Fuzzy Controller outputs will produce based on the rules that would be structured based on human experience. Whereas, ANFIS is the best trade-off between neural and fuzzy system which provide smoothness, due to the fuzzy controller (FC) interpolation and adaptability due to the neural network (NN)[7].

Nowadays, there are advanced developments in neuro-fuzzy synergisms for modelling and adaptive control of nonlinear systems [5].

Using training data, ANFIS constructs a fuzzy inference system whose membership functions parameters are tuned using either a back propagation algorithm alone, or in combination with recursive least squares type algorithm. Using hybrid learning technique, the learning process speeds up compared to the gradient method alone, which exhibits the tendency to be trapped in local minima [3].

For simplicity, we assume the fuzzy inference system under consideration has two inputs x and y and one output z. We suppose that the rule base contains two fuzzy *if-then* rules of Takagi and Sugeno's type [4].

Rule 1: If x *is* A_1 *and* y *is* B_1 *then* $f_1=p_1 x+ q_1 y + r_1$

Rule 2: If x *is* $A2$ *and* y *is* $B2$ *then* $f2=p_2 x+ q_2 y + r_2$

Then type-3 fuzzy reasoning is illustrated in Figure 2(a) and the corresponding equivalent ANFIS architecture is shown in Figure 2(b).

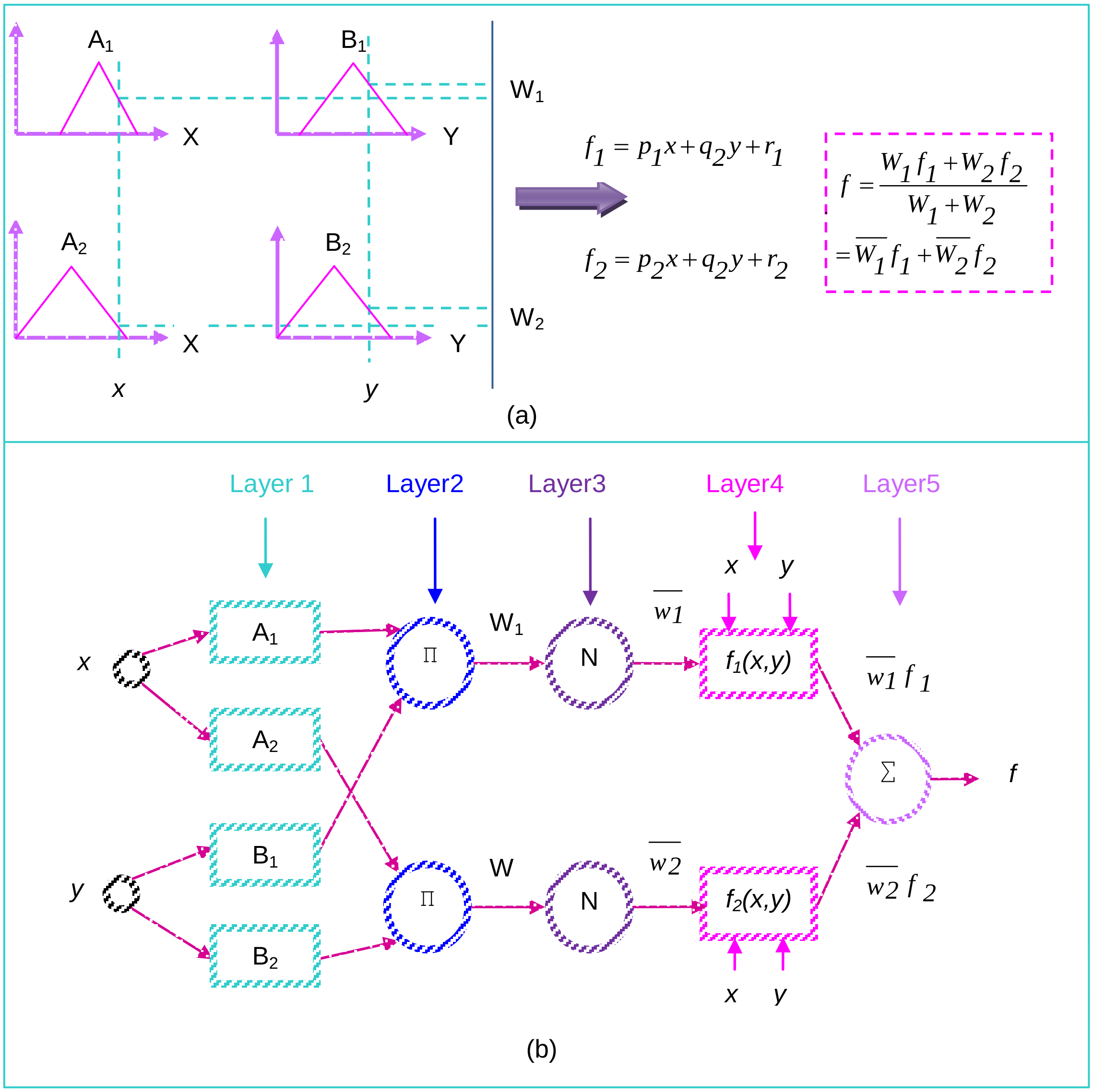


Figure 2. (a) Type-3 fuzzy reasoning, (b) Equivalent ANFIS

The node functions in the same layer are of the same function family as described below [4]:

Layer 1: Every node *i* in this layer is a square node with a node function [4]:

$$O_i^1 = \mu_{A_i}(x) \qquad For\ i=1,2,\ldots. \tag{4}$$

Where *x* is input to node *i* and A_i is the linguistic label associated with this node function.

Layer 2: Every node in this layer is a circle node labelled *Π* which multiplies the incoming signals and the product out. For instance [4],

$$\omega_i = \mu_{A_i}(x) \times \mu_{B_i}(x) \qquad i=1,2. \tag{5}$$

Each node output represents the firing strength of a rule [4].

Layer 3: Every node in this layer is a circle node labelled *N*, the *i*th node calculates the ratio of the *i*th rule's firing strength [4]:

$$\overline{\omega_i} = \frac{\omega_i}{\omega_1 + \omega_2} \qquad i=1,\,2. \tag{6}$$

Layer 4: Every node *i* in this layer is a square node with a node function [4]:

$$O_i^4 = \overline{\omega_i} f_i = \overline{\omega_i}(\,p_i x + q_i y + r_i\,) \tag{7}$$

Layer 5: The single node in this layer is a circle node labelled $\sum$ that computes the overall output as summation of all incoming signals, *i.e.* [4],

$$O_1^5 = \sum_i \overline{\omega_i} f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} = \text{overall output} \tag{8}$$

Proposed strategy is introduced in next section.

4. Proposed Controller

Proposed controller is structure by ANFIS therefore three ANFIS controllers are needed for determining the values of K_p, K_i, K_d because each of ANFIS controllers should have only one output. The proposed controller coefficients (K_p, K_i, K_d) are selected according to values of error *(e)* and error derivative *(de/dt)*. The block diagram of proposed method is as follows:

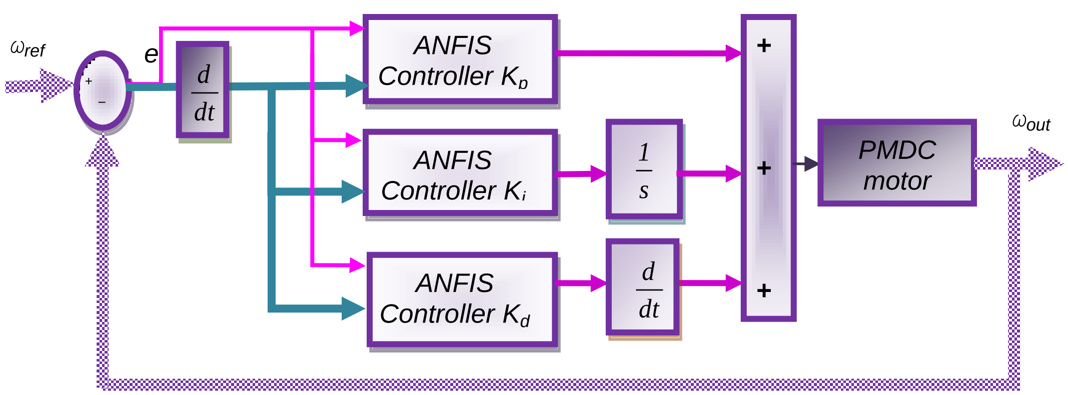
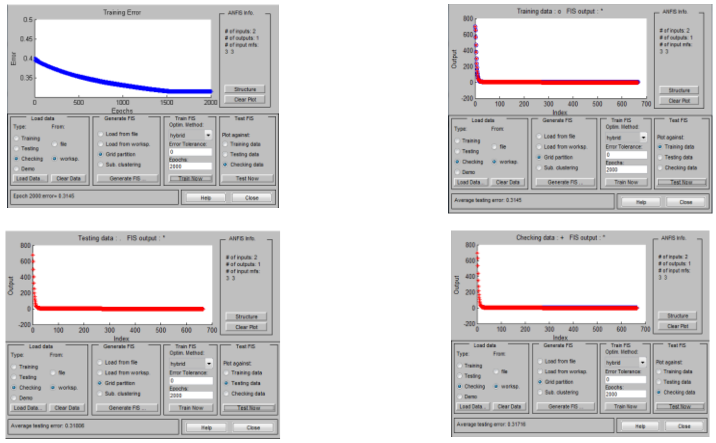


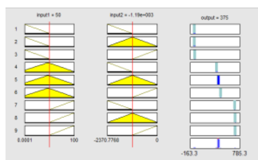
Figure 3. Proposed control strategy

2001 input-output pairs are applied for training, testing and checking each of the ANFIS controller (Data number can be changed). Each of ANFIS controllers uses grid partition to generate fuzzy inference system. Figure 4, Figure 5 and Figure 6 show properties of ANFIS controllers.

The Figure 4 shows that three triangle input membership functions and nine constant output membership functions are used in ANFIS controller when hybrid method is used to optimization method. The training, checking and testing errors can quantitatively be expressed respectively equal to: 0.3145, 0.31716 and 0.31806.



(a)



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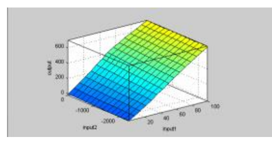
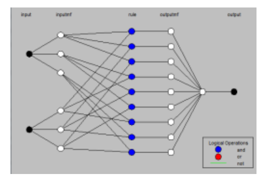
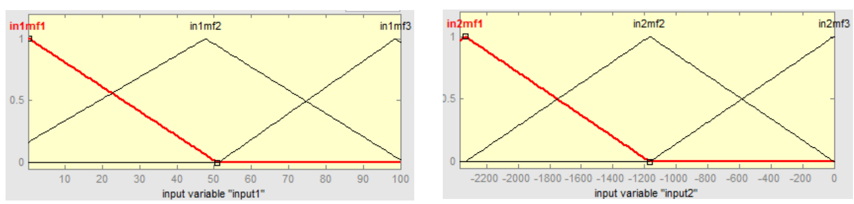


(c)



(d)



(e)

Figure 4. (a) Results of ANFIS training, checking and testing (K_p), (b) Rule viewer (K_p), (c) Surface viewer (K_p), (d) ANFIS Model Structure (K_p), (e) Input membership functions

Fuzzy inference system is used nine *if-than* rules to describe all possible conditions. The fuzzy rules of the K_p ANFIS controller are as below:

Table 1. Fuzzy rules of K_p controller

de / e	In2mf1	In2mf2	In2mf3
In1mf1	-84.28	-76.35	-69.75
In1mf2	348.3	384.6	421.5
In1mf3	697.8	705	706.2

K_i and K_d ANFIS controllers use same optimization method, input and output membership functions numbers. The Figure 5 shows that the training, checking and testing errors can quantitatively be expressed respectively equal to: 0.070259, 0.074447 and 0.074208.

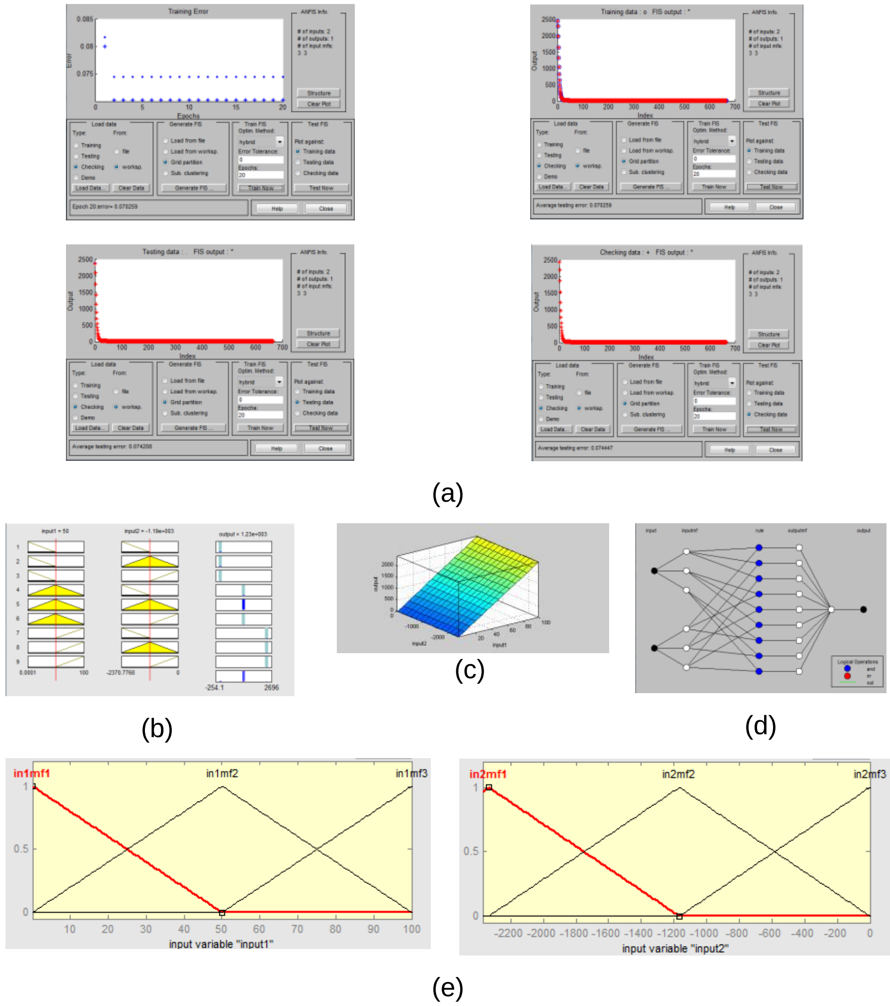


Figure 5. (a) Results of ANFIS training, checking and testing (*K_i*), (b) Rule viewer (*K_i*), (c) Surface viewer (*K_i*), (d) ANFIS Model Structure (*K_i*), (e) Input membership functions

The K_i ANFIS controller contains nine *if-than* rules that these are as below:

Table 2. Fuzzy rules of K_i controller

de / e	In2mf1	In2mf2	In2mf3
In1mf1	-8.251	-3.364	0.0115
In1mf2	1224	1228	1231
In1mf3	2450	2449	2450

The Figure 6 shows that the training, checking and testing errors can quantitatively be expressed respectively equal to: 0.00053394, 0.00070392 and 0.00099541. The K_d ANFIS controller uses hybrid method for optimization. ANFIS controller applies three membership functions for each of inputs.

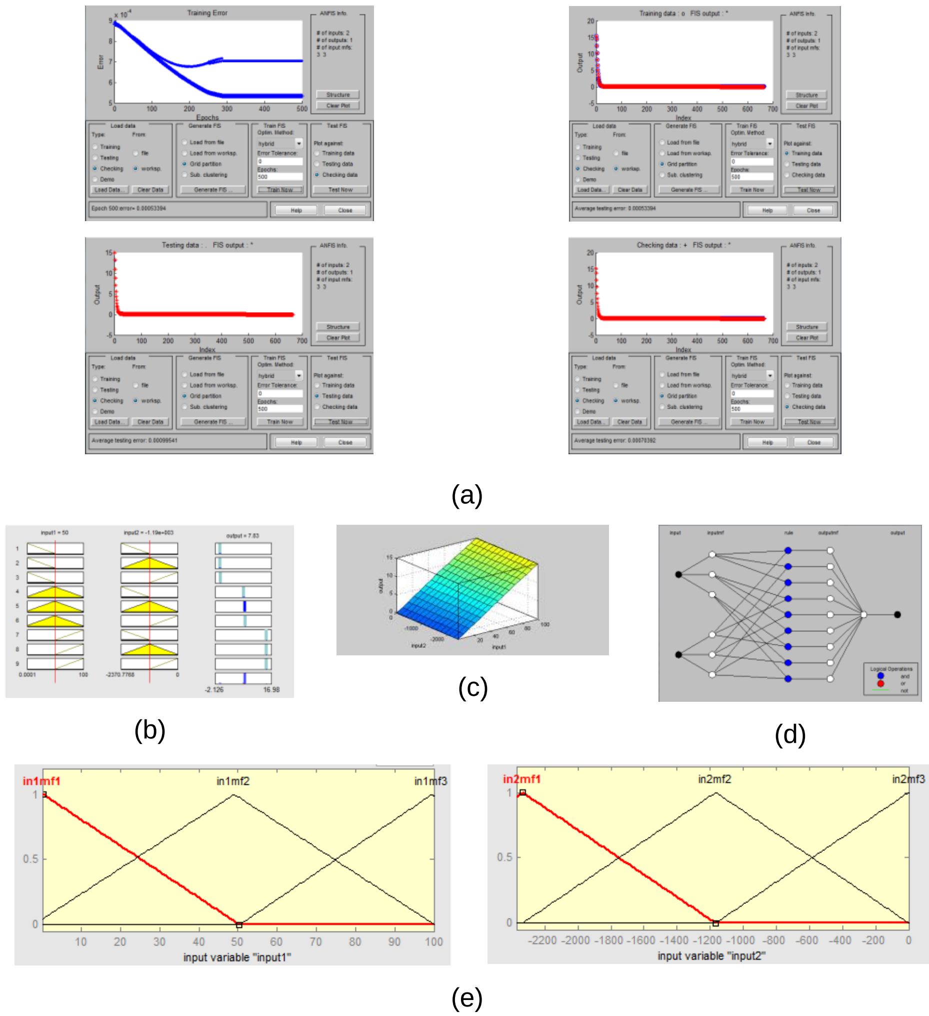


Figure 6. (a) Results of ANFIS training, checking and testing (K_d), (b) Rule viewer (K_d), (c) Surface viewer (K_d), (d) ANFIS Model Structure (K_d), (e) Input membership functions

Table 3 is obtained after training ANFIS controller (K_d). The fuzzy rules table shows that nine *if-than* rules describe all possible conditions.

Table 3. Fuzzy rules of K_d controller

de / e	In2mf1	In2mf2	In2mf3
In1mf1	-0.5343	-0.4472	-0.3502
In1mf2	7.681	7.9	8.087
In1mf3	15.3	15.38	15.38

Grid partition is used to generate FIS when hybrid method is used for optimization. Each of three ANFIS controllers uses nine *if-than* rules. The ANFIS controllers can improve motor performance characteristics in different conditions. Next section describes simulation results also we discuss about results.

5. Simulation Results and Discussion

Permanent magnet DC motor parameters are as follows:

R_A=7.72 (ohm), L_A= 0.16273 (H), K_T=1.25 (Nm), B_M=0.003 (N.m.s/r) and J_M= 0.0236 (kg.m^2). First, the step response of without controller closed loop system is investigated. Figure 7 shows step responses of PMDC motor in no load, increasing reference speed, applied load and noisy load conditions.

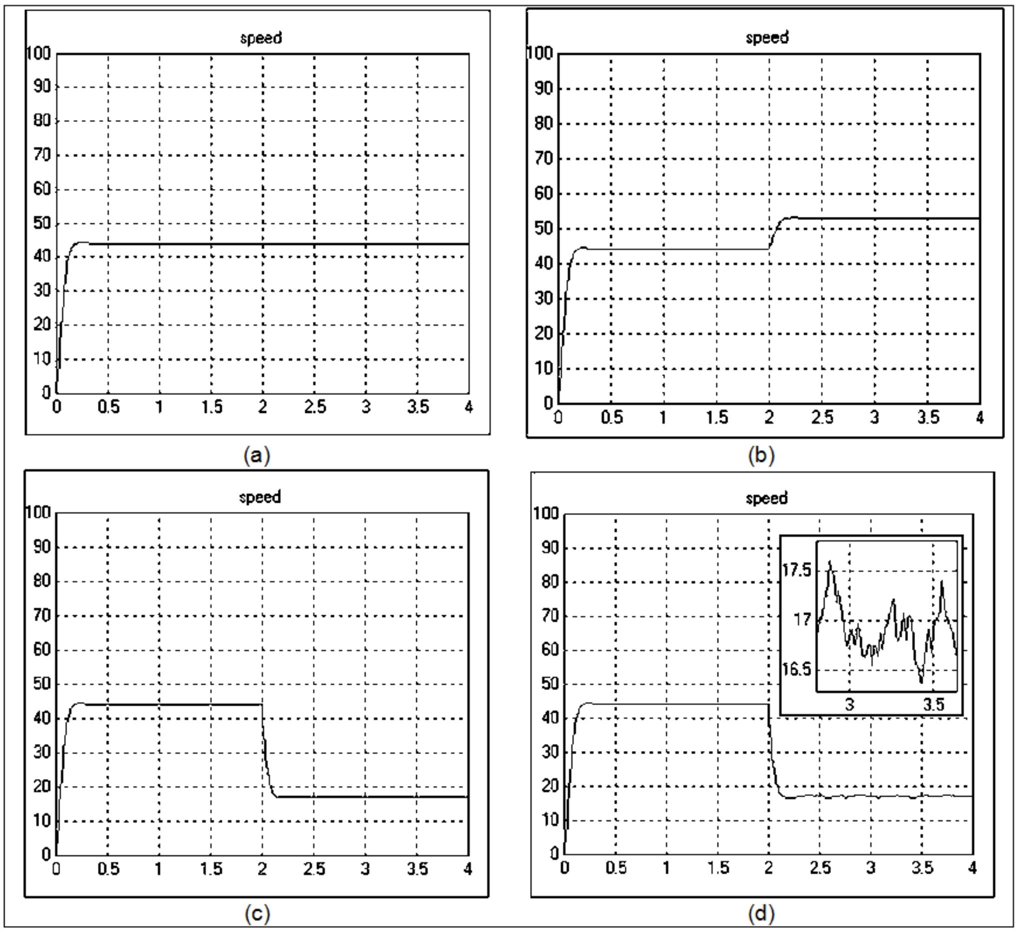


Figure7. Step response of closed loop system (a) no load, (b) increasing reference speed, (c) applied load, (d) applied noisy load

The Figure 7 shows that steady state error is very large in no load also steady state speed aren't desirable in applied load and increasing reference speed conditions. Step response doesn't have reasonable behaviour in noisy load condition (Load applies in t=2s; Speed increases in t= 2s, new reference speed = 120 rad/s and noise power = 0.001).

In this section, step responses of control systems based on IMC PID and proposed controllers are investigated in different conditions. Internal Model Control [9] method is used to design PID controller.

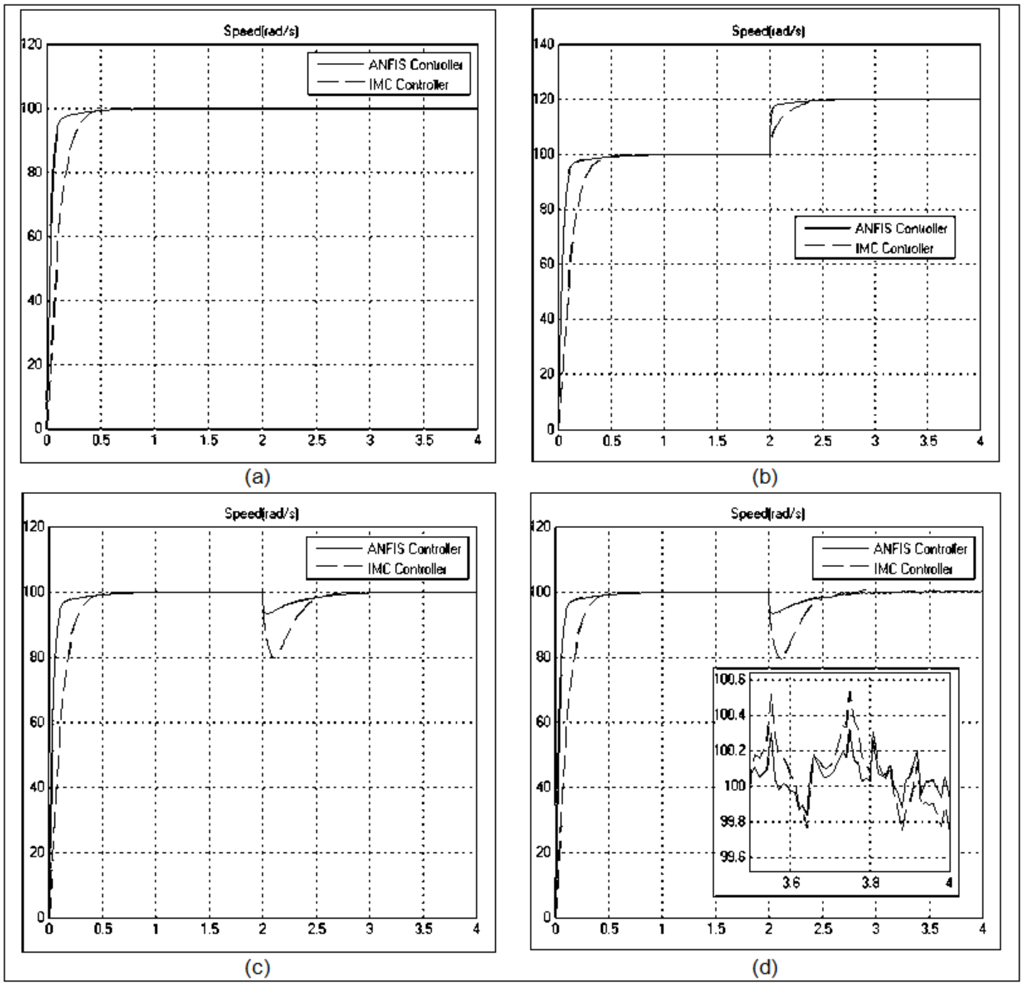


Figure 8. Step response of proposed and IMC PID controllers in different conditions (a) no load, (b) increasing reference speed, (c) applied load, (d) applied noisy load

Figure 8(a) shows that proposed controller based system has shorter rise time and settling time than IMC controller based system. The steady state error and percent maximum overshoot of control system based on proposed and IMC controllers equal zero. Figure 8(b) shows that rise time of control system based on proposed controller is shorter than IMC controller based system in increasing reference speed condition (Speed is increased in t=2s and new reference speed=120 rad/s). Figure 8(c) shows that proposed controller based system has smaller percent minimum speed due to applying load (MSDAL) while recovery time is shorter (load is applied in t= 2s and T_L=10N). Figure 8(d) shows that control system based on proposed controller has less percent oscillations in noisy load condition than IMC controller based system (Noise power= 0.001). The rise time, settling time, steady state error and percent maximum overshoot are shown in Table 4. The rise time and final speed of increasing reference speed condition, recovery time, percent minimum speed due to appling load and percent oscillation are given in Table 5.

Table 4. Step response performance characteristics of control systems (no load)

Method	Rise time (s)	Settling time (s)	Maximum overshoot (%)	Steady state error (%)
Without controller	0.1024	0.1637	0.33	55.9186
IMC controller	0.2191	0.3983	0	0
Proposed controller	0.0761	0.2508	0	0

Table 4 shows that proposed controller based system has shorter rise time than without controller system, when control system based on proposed controller has smaller percent overshoot and steady state error than without controller system. IMC controller based system improves percent overshoot and steady state error but rise time and settling time values are undesirable. The settling time of proposed controller based system is longer than the without controller system but settling time of proposed controller is reasonable. Others performance characteristics are shown in Table 5.

Table 5. Performance characteristics of control systems in different conditions

Condition	increasing reference speed (New reference speed =120 rad/s , applied time = 2s)		Applied load (Applied time= 2s, T_L=10 N)		Noise (Noise power =0.001)
Method	Final speed (rad/s)	Rise time (s)	Recovery time (s)	Percent minimum speed due to applying load (%)	Percent oscillations (%)
Without controller	52.8977	0.1024	------------	---------------	7.474
IMC controller	120	0.3064	0.5198	20.3046	0.7897
Proposed controller	120	0.0781	0.4581	6.6844	0.4892

Table 5 shows that proposed controller based system improves system behaviour in increasing reference speed, applied load and noise conditions. The percent minimum speed due to applying load and oscillations of control system based on IMC are smaller than performance criteria of without controller system when recovery time of IMC based control system is shorter than recovery time of without control system. Table 5 shows that proposed controller shows better behaviour in all conditions.

6.Conclusion

By applying our proposed controller, performance characteristics are meaningly improved. The improvements include modifying system behaviour characteristics in no load condition, i.e. rise time from 0.1024s to 0.0761s and percent steady state error form 55.9186% to 0%. When comparing to IMC controller based system shows high speed to reach desired value, short recovery time and less percent minimum speed due to applying load and oscillations can consider as advantages of the proposed controller. Exactly, motor speed reduction due to applying load of proposed controller is smaller than IMC based control system while recovery time to reference motor speed of proposed system is shorter too, i.e. rise time to reach new reference speed from 0.3064s to 0.0781s and recovery time 0.5198s to 0.4581s.

Finally, we could announce that the system with applying our proposed controller shows more rational characteristics performance when reasonable implementation should be kept in mind as an extra advantages.The ANFIS controller uses Sugeno inference therefore fuzzy computation time is decreased whereas Mamdani fuzzy inference uses longer time for fuzzy computation. ANFIS controllers uses fewer fuzzy rule set therefore proposed system has reasonable implementation. According to what was mention, the proposed controller can improve system behaviour in different conditions, moreover proposed system has easy implementation.

Acknowledgements

The Authors thank ISLAMIC AZAD University, Central Tehran Branch as this work is the result of master thesis in electrical engineering (MSc Eng.) with titled "Improvement Performance of Permanent Magnet Motor by Using Fuzzy Controller" which is on focus at the Faculty of Engineering.

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