Adaptive Neuro-Fuzzy Speed Controller for Vector Controlled Induction Motor Drive

Rajesh Kumar [1] R. A. Gupta [2] Rajesh S. Surjuse [3]

Abstract– This paper presents a novel adaptive neuro-fuzzy based speed controller for vector controlled induction motor drive. The proposed neuro-fuzzy controller incorporates fuzzy logic algorithm with a five-layer artificial neural network (ANN) structure. The conventional PI controller is replaced by Adaptive Neuro-Fuzzy Inference System (ANFIS), which tunes the fuzzy inference system with hybrid learning algorithm. This makes fuzzy system to learn. The performance of the proposed neuro-fuzzy based vector controlled induction motor drive is investigated at different operating conditions. The results of the proposed controller are also compared to those obtained by a conventional PI controller and Fuzzy Logic controller. The simulation study indicates robustness and suitability of drive for high performance drive applications.

Keywords – Adaptive Neuro-Fuzzy Inference System(ANFIS), Artificial Neural Network (ANN), back propagation algorithm, hybrid learning algorithm

I. INTRODUCTION

Vector controlled induction motor (IM) drive is a very accepted method for high performance system response [1]-[2]. This method employs the conventional Proportional – Integral (PI), Proportional – Integral – Derivative (PID) controller or their adaptive versions, for variable speed drive applications. However, the design of these controllers depends on exact mathematical model with accurate parameters. The difficulties of obtaining the exact parameters of the induction motor leads to cumbersome design approach. Also the conventional fixed gain PI and PID controllers are very sensitive to disturbances, parameter variations and system non-linearity. On the other hands, the design of intelligent controllers based on Artificial Intelligence (AI) does not need the exact mathematical model of the system. Therefore Artificial Neural Network (ANN) and Fuzzy Logic Control (FLC) demands special attention for speed control of high performance IM drives.

Fuzzy Logic Controller yields superior and faster control [3]-[4], without the need of accurate mathematical model of the system and works well for complex, non-linear, multi-dimensional system with parameter variations or with less precise signals. The main design problem lies in the determination of consistent and complete rule set and shape of the membership functions. A lot of trial and error has to be carried out to obtain the desired response which is time consuming. On the other hand, ANN alone is insufficient if the training data are not enough to take care of all the operating modes.

Adaptive Neuro-Fuzzy Inference System (ANFIS) is used as an intelligent tool to design FLC [5]-[11]. It helps to generate and optimize membership functions as well as the rule base from the simple data provided. ANFIS combine the learning power of neural network with knowledge representation of fuzzy logic. This paper presents a novel speed control scheme of vector controlled IM drive based on Neuro-fuzzy controller (NFC) [12]-[14]. The proposed NFC is adapted by a hybrid learning algorithm in order to minimize the square of the error between desired and actual output. A 5-layer ANN structure is utilized to train the parameters of the FLC, which eliminates unwanted trial and error as was in the case for a conventional fuzzy logic control. A complete simulation model for vector controlled IM drive incorporating the proposed NFC was developed. The performance of the proposed NFC based IM drive has been investigated at different operating conditions. A comparison is made with the conventional PI speed controller and Fuzzy Logic speed controller response. Section II presents the mathematical modeling of IM and vector control scheme. Section III presents the design aspects of proposed NFC. Section IV and V presents the performance evaluation and conclusion respectively.

II. VECTOR CONTROLLED INDUCTION MOTOR DRIVE

Induction Motor Modeling

The mathematical model of a three- phase squirrel cage induction motor in synchronous rotating reference frames is given by equations (1)-(11) as follows [2].

$$V_{ds}^{e} = R_s . i_{ds}^{e} + p\lambda_{ds}^{e} + w_e . \lambda_{qs}^{e} \quad (1)$$

$$V_{qs}^{e} = R_s . i_{qs}^{e} + p\lambda_{qs}^{e} - w_e . \lambda_{ds}^{e} \quad (2)$$

$$0 = R_r . i_{dr}^{e} + p\lambda_{dr}^{e} - (w_e - w_r).\lambda_{qr}^{e} \quad (3)$$

$$0 = R_r . i_{qr}^{e} + p\lambda_{qr}^{e} + (w_e - w_r).\lambda_{dr}^{e} \quad (4)$$

Where

$$\lambda_{ds}^{e} = L_s . i_{ds}^{e} + L_m i_{dr}^{e} \quad (5)$$

$$\lambda_{qs}^{e} = L_s . i_{qs}^{e} + L_m i_{qr}^{e} \quad (6)$$

$$\lambda_{dr}^{e} = L_r . i_{dr}^{e} + L_m i_{ds}^{e} \quad (7)$$

$$\lambda_{qr}^{e} = L_r . i_{qr}^{e} + L_m i_{qs}^{e} \quad (8)$$

and electromagnetic torque

$$T_e = \frac{3}{2}\frac{P}{2} L_m (i_{qs}^{e} i_{dr}^{e} - i_{ds}^{e} i_{qr}^{e}) \quad (9)$$

$$\frac{d\theta_r}{dt} = \omega_r \quad (10)$$

$$T_e = J_m \frac{d\omega_r}{dt} + B_m \omega_r + T_L \quad (11)$$

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where v_{ds}^e, v_{qs}^e are d-q axis stator voltages respectively; $i_{ds}^e, i_{qs}^e, i_{dr}^e, i_{qr}^e$ are d-q axis stator currents and d-q axis rotor currents respectively; R_s, R_r are the stator and rotor resistance per phase respectively; L_s, L_r, L_m are the self inductances of the stator and rotor and the mutual inductance respectively; P is the number of poles; p is the differentiation operator *(d/dt)*; ω_e, ω_r are the speed of the rotating magnetic field and the rotor speed respectively; T_e, T_L are the electromagnetic developed torque and the load torque respectively; J_m is the rotor inertia; B_m is the rotor damping coefficient and θ_r is the rotor position.

The transformation from abc to dq0 variables is given by equation (12).

$$f_{dq0} = \left[T_{abc}^e\right] f_{abc}^e \tag{12}$$

$$\left[T_{abc}^e\right] = \frac{2}{3}\begin{bmatrix} cos(\omega t) & cos(\omega t-\frac{2\Pi}{3}) & cos(\omega t+\frac{2\Pi}{3}) \\ sin(\omega t) & sin(\omega t-\frac{2\Pi}{3}) & sin(\omega t+\frac{2\Pi}{3}) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \tag{13}$$

where $\left[T_{abc}^e\right]$ is transformation matrix given by equation (13) and f may represents current or voltage.

Vector Control

For high performance drive system response, the vector controlled induction motor is a very accepted method [2]. It is based on the decoupling of flux and torque producing components of the stator current. Under this condition, the q-axis component of rotor flux is set to zero while the d-axis reaches the nominal value of the magnetizing flux. The torque equation can also be written as

$$T_e = \frac{3}{2}\frac{P}{2}\frac{L_m}{L_r}(i_{qs}^e \lambda_{dr}^e - i_{ds}^e \lambda_{qr}^e) \tag{14}$$

Since λ_{qr}^e is zero

$$T_e = \frac{3}{2}\frac{P}{2}\frac{L_m}{L_r}(i_{qs}^e \lambda_{dr}^e) = K_{te} i_{qs}^e \lambda_{dr}^e \tag{15}$$

where $K_{te} = \frac{3}{2}\frac{P}{2}\frac{L_m}{L_r}$ = torque constant

If the rotor flux linkage in equation (15) is maintained constant, then the torque is simply proportional to the torque producing component of the stator current, as in the case of the separately excited dc machine with armature current control. From equations (3), (4) and (7), (8) putting λ_{qr}^e equal to zero, other field oriented controller equations are obtained as

$$T_r \frac{d\lambda_{dr}^e}{dt} + \lambda_{dr}^e = L_m i_{ds}^e \tag{16}$$

$$\omega_e = \frac{L_m}{T_r}\frac{i_{qs}^e}{\lambda_{dr}^e} + \omega_r \tag{17}$$

T_r denotes the rotor time constant. The equation (16) resembles the field equation in a separately excited dc machine, whose time constant is usually in the order of seconds. Likewise, the induction motor rotor time constant is in the order of seconds.

The equations which transform the synchronous reference frame to stationary reference frame are:

$$i_{qs}^s = \cos\theta_e i_{qs}^e + \sin\theta_e i_{ds}^e \tag{18}$$

$$i_{ds}^s = -\sin\theta_e i_{qs}^e + \cos\theta_e i_{ds}^e \tag{19}$$

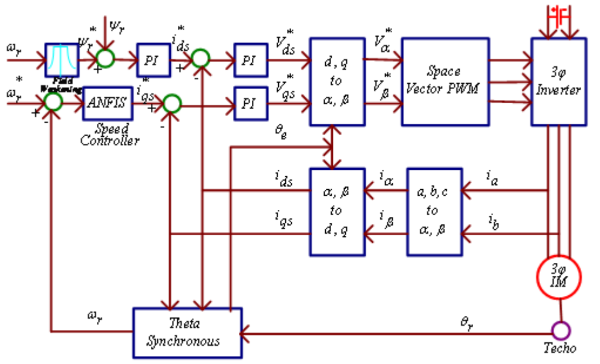


Fig. 1. Adaptive Neuro-Fuzzy speed controller based vector controlled induction motor drive.

where i_{qs}^s, i_{ds}^s are stationary frame q and d axis stator current respectively. The proposed vector control scheme is depicted in Fig. 1.

III. ADAPTIVE NEURO-FUZZY CONTROLLER

The proposed neuro-fuzzy controller incorporates fuzzy logic algorithm with a five layer artificial neural network (ANN) structure [13] as shown in fig. 2.

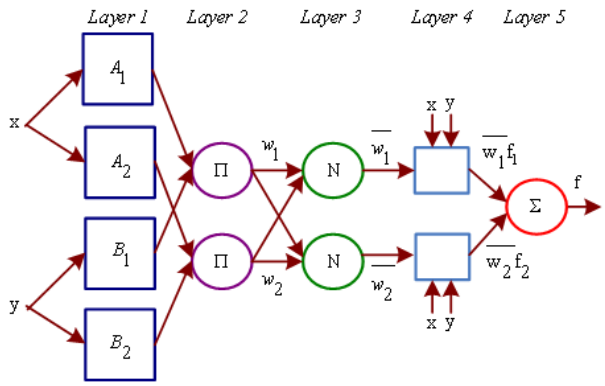


Fig. 2. ANFIS architecture of 2-input Sugeno fuzzy model with 2 rules.

A tuning block is utilized to adjust fourth layer's parameters in order to correct any deviation of control effort. The speed error and the rate of change of actual speed error are the inputs of the neuro-fuzzy controller, which are given by

$$Input1 = \varepsilon_\omega = \omega^* - \omega \tag{20}$$

$$Input2 = \Delta\varepsilon_\omega = \frac{\varepsilon_\omega(n) - \varepsilon_\omega(n-1)}{T} x100\% \tag{21}$$

where ω^* is the command speed and T is the sampling time.

Sugeno fuzzy model with five- layer ANN structure is used in proposed controller. In this five-layer ANN structure the first layer represents for inputs, the second layer represents for fuzzification, the third and fourth layers represents for fuzzy rule evaluation and the fifth layer represents for defuzzification.

A two input first order Sugeno fuzzy model with two rules is depicted in fig. 2.

In layer 1, every node i is an adaptive node with a node function

$$O_{1,i} = \mu_{Ai}(x) \text{ for } i=1,2 \text{ or}$$

$$O_{1,i} = \mu_{Bi-2}(y) \text{ for } i=3,4 \qquad (22)$$

(here we denote the output of the ith node in layer 1 as $O_{1,i}$)

where x (or y) is the input to node i and A_i *(or* B_{i-2}*)* is a linguistic label such as 'small' or 'large' associated with this node. The membership function for A can be any appropriate parameterized membership function. In proposed scheme generalized bell function is used as a membership function given by equation (23).

$$\mu_A(x) = \left(1 \Big/ 1 + \left| \frac{x - c_i}{a_i} \right|^{2bi} \right) \qquad (23)$$

where $\{a_i, b_i, c_i\}$ is the parameter set. As the values of these parameters changes, various forms of bell shaped membership functions can be get for fuzzy set A. Parameters in this layer are referred to as premise parameters.

In layer 2 , every node is a fixed node labeled Π , whose output is the product of all the incoming signals.

$$O_{2,i} = w_i = \mu_{Ai}(x)\mu_{Bi}(y) \;,\; i=1,2 \qquad (24)$$

Each node output represents the firing strength of a rule.

In layer 3, every node is a fixed node labeled N. The outputs of this layer are normalized firing strengths given by equation (25).

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \;,\; i=1,2 \qquad (25)$$

In layer 4, every node i , is an adaptive node with a node function given by equation (26).

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \qquad (26)$$

where $\overline{w}_i$ is a normalized firing strength from layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set of this node. Parameters in this layer are referred to as consequent parameters.

Layer 5 is the single node layer with a fixed node labeled Σ , which computes the overall output as the summation of all incoming signals.

$$O_{5,1} = \sum_i \overline{w}_i f_i = \frac{\Sigma_i w_i f_i}{\Sigma_i w_i} \qquad (27)$$

Hybrid learning algorithm [14] is used in proposed controller. It has two passes, forward pass and backward pass. In the forward pass of the hybrid learning algorithm, node output goes forward until layer four and the consequent parameters are identified by the sequential least squares method. In the backward pass, the error signals propagate backward and premise parameters are updated by gradient descent that is back propagation learning method. The consequent parameters thus identified are optimal under the condition that the premise parameters are fixed. Thus, the hybrid approach converges much faster since it reduces the search space dimension of the original pure back propagation.

In hybrid learning, for back propagation, objective function to be minimized is defined by (28).

$$E_p = \sum_{m=1}^{\ell} (T_{m,p} - O_{m,p})^2 \qquad (28)$$

where $T_{m,p}$ is the mth component of pth target output vector and $O_{m,p}$ is the mth component of actual output vector produced by the presentation of the pth input vector.

Hence the over all error measure is given by (29).

$$E = \Sigma_{p=1}^{P} E_P \qquad (29)$$

Learning rules can be derived as follows

$$a_i(n+1) = a_i(n) - \eta_{ai}(\partial E / \partial a_i) \qquad (30)$$

$$b_i(n+1) = b_i(n) - \eta_{bi}(\partial E / \partial b_i) \qquad (31)$$

$$c_i(n+1) = c_i(n) - \eta_{ci}(\partial E / \partial c_i) \qquad (32)$$

where η_{ai} , η_{bi} and η_{ci} are the learning rates of the

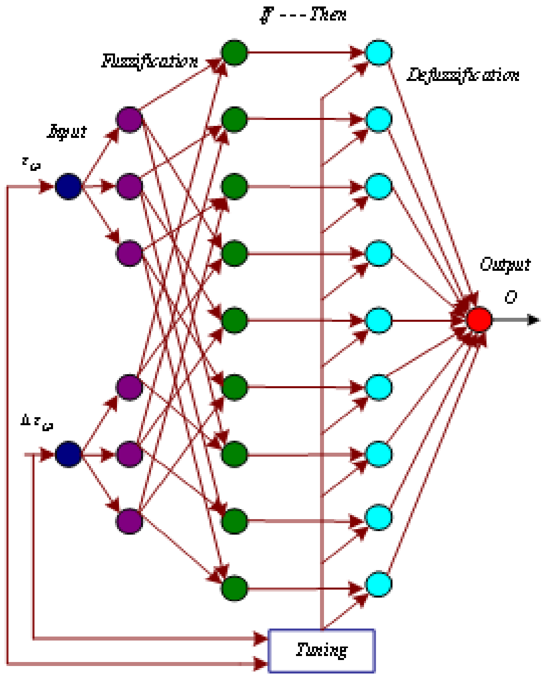


Fig. 3. Proposed equivalent ANFIS architecture

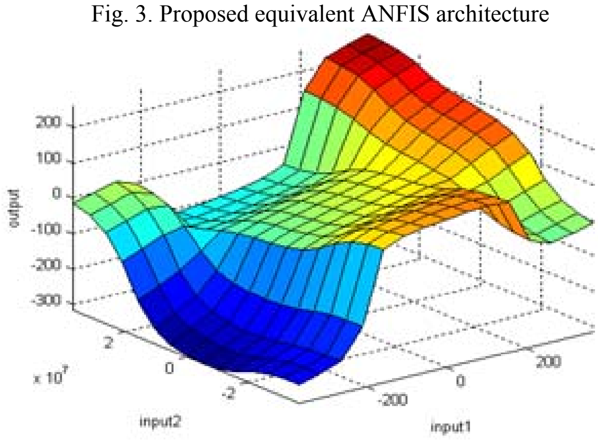


Fig. 4. Output surface of proposed ANFIS

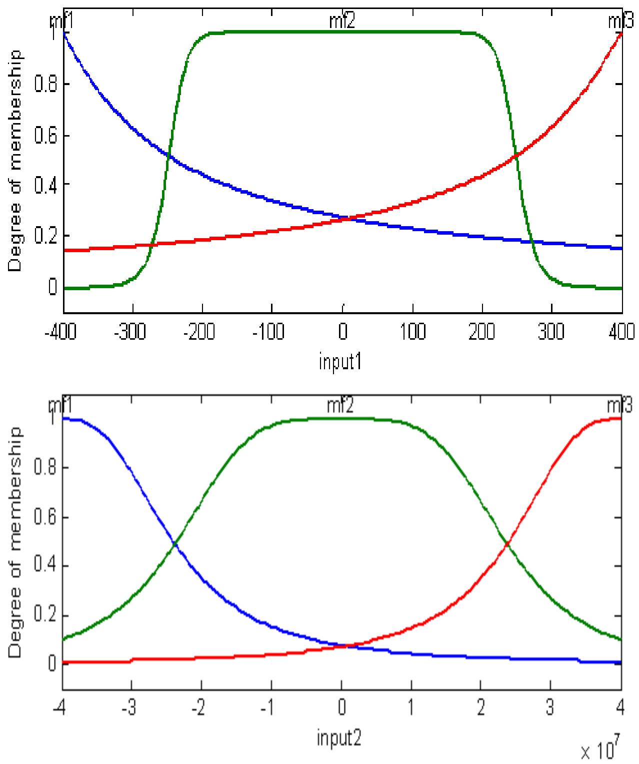


Fig. 5. Input membership function of proposed ANFIS

corresponding parameters. The derivatives in the above equations can be found by chain rule.

The propose ANFIS had following features: Type-Sugeno; AndMethod- product; OrMethod- probor (probabilistic or); DefuzzMethod- wtaver (weighted average); ImpMethod (implication method)- product; AggMethod (aggregation method)- sum; No. of input- 2; No. of input membership function- 3; input membership function type- gbellmf (generalized bell curve membership function); No. of output- 1; No. of output membership function- 9; output membership function type - linear; No. of rules- 9. Fig. 3. presents proposed equivalent ANFIS architecture. Fig. 4. and Fig. 5. shows output surface and input membership functions of proposed ANFIS respectively.

IV. Performance Assessment of Neuro-Fuzzy Controller Based Vector Controlled IM Drive

A complete simulation model for vector controlled IM drive incorporating the proposed NFC is developed.

The performance of the proposed NFC based IM drive is investigated at different operating conditions. In order to prove the superiority of the proposed NFC, a comparison is made with the response of conventional PI and FLC speed controller based IM drive. The parameters of the induction motor considered in this study are summarized in Appendix A. The design parameter of PI speed controller is given in Appendix B and for FLC speed controller is given in Appendix C. The performance of vector control induction motor drive with all the three speed controller are presented during starting, load perturbation and speed reversal. Transient, steady state and dynamic behavior of the drive with PI speed controller is shown in Fig. 6, with FLC speed controller is shown in Fig. 7 and with neuro-fuzzy speed controller is shown in Fig. 8. The reference speed is set at 185 rad/sec. The electromagnetic torque Te rises to maximum during starting of the motor from standstill and then settles down over remaining period (steady state condition). Same is for currents. At steady state load torque T_L has been increased to 12 Nm from 3 Nm at time t=0.3 sec. and suddenly decreased to 3 Nm at t=0.5 sec. Finally the motor which is operating at 185 rad/sec, suddenly its reference speed is changed to negative 185 rad/sec. Table I, II and III presents performance comparison during steady state operation, during transient operation and in time domain analysis respectively.

Table 1: Performance comparison during steady state operation

Controller	Speed Ripple (rad/sec)	Torque Ripple (Nm)
PI	**0.1**	**0.0017**
FLC	**0.008**	**0.0005**
NFC	**0.004**	**0.0003**

Table 2: Performance comparison during transients

Controller	Starting Time (sec)	Reversal Time (sec)	Dip in Speed (rad/sec)	Rise in Speed (rad/sec)
PI	0.04	0.145	4.9	4.8
FLC	0.032	0.11	4.78	4.63
NFC	0.03	0.08	4.7	4.6

Table 3: Performance comparison in time domain analysis

Controller	Peak Over shoot	Peak Time (sec)	Rise Time (sec)	Settle Time (sec)
PI	0.1351	0.06	0.03	0.13
FLC	0.08	0.058	0.028	0.128
NFC	0.0054	0.057	0.026	0.11

The results shows better performance of NFC based IM drive as compare to conventional PI and FLC controller based IM drive under starting, load perturbation and speed reversal. Since fuzzy logic has tolerance for imprecision of data and neural network has tolerance for noisy data, their combination neuro-fuzzy is having good tolerance for the parameter variation particularly stator and rotor resistances.

Also, neuro-fuzzy controller is universal function approximator, it can very well approximate linear and non-linear functions, thus it is more versatile than a linear controller in dealing with nonlinear plant characteristics and hence it has better stability than the conventional linear controller. Above discussion shows NFC based vector control induction motor drive is robust for high performance IM drive.

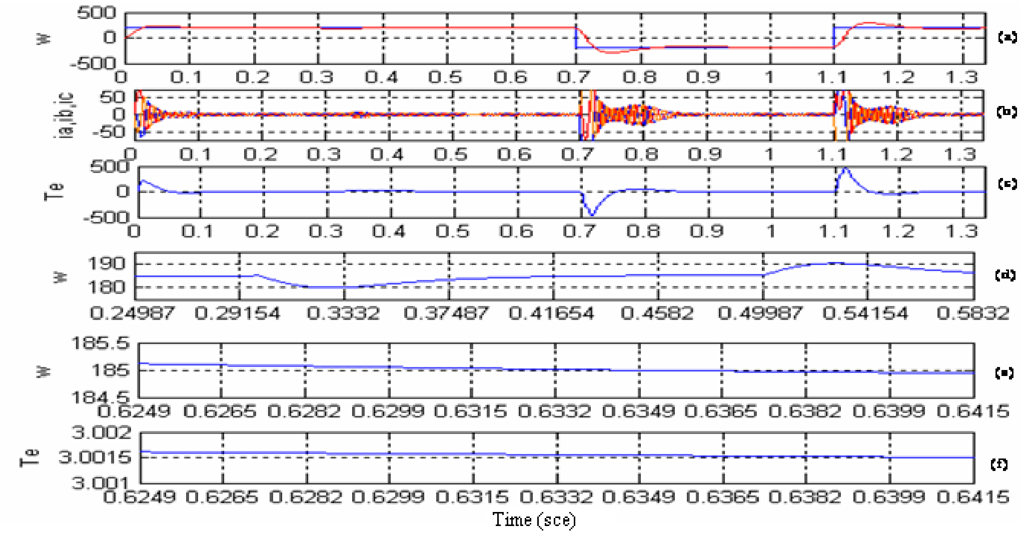


Fig.6. Performance Characteristics of Drive Scheme with PI- Speed controller (a) speed (rad/sec.) (b) current (amp.) (c) torque (Nm) (d) speed during loading cycle (e) speed ripples (f) torque ripples.

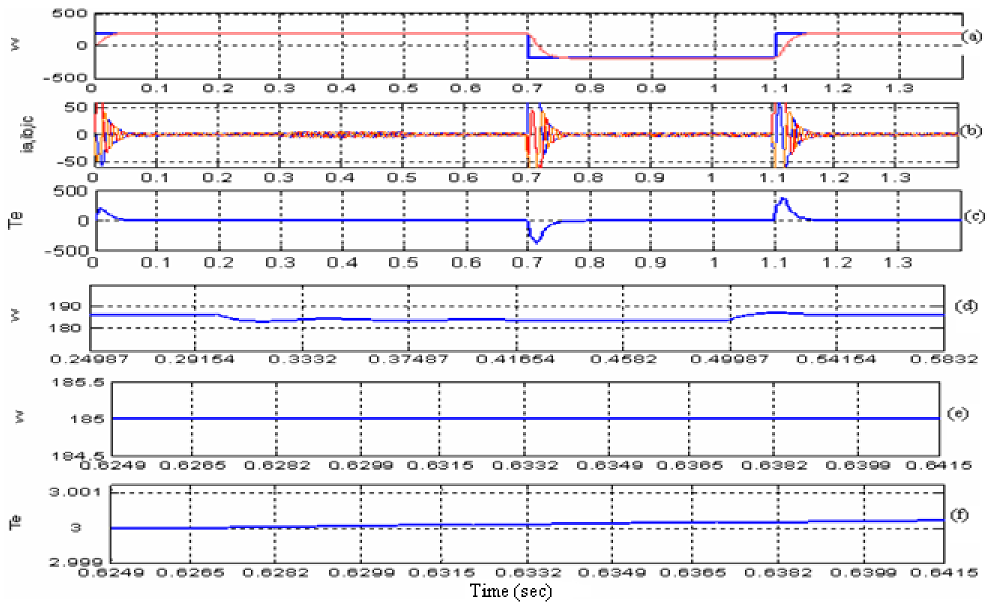


Fig.7. Performance Characteristics of Drive Scheme with FLC- Speed controller (a) speed (rad/sec.) (b) current (amp.) (c) torque (Nm) (d) speed during loading cycle (e) speed ripples (f) torque ripples

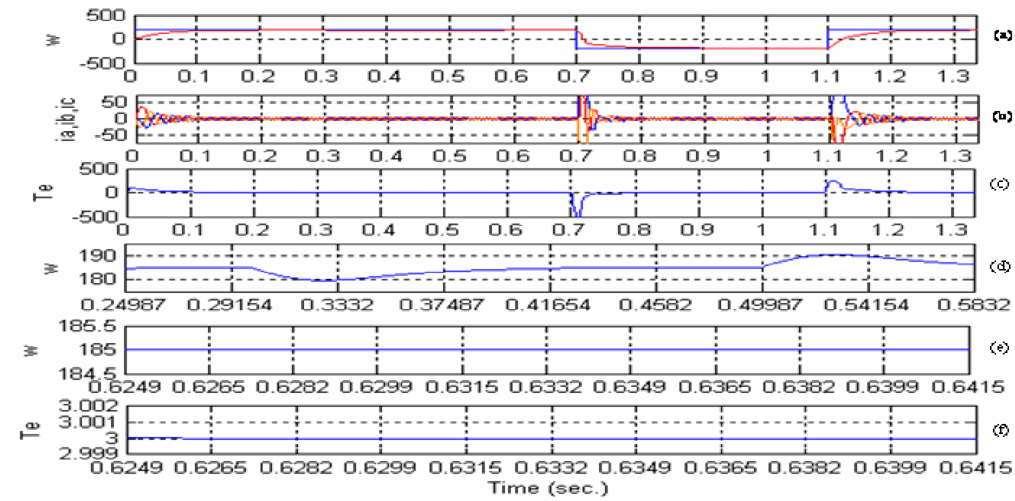


Fig. 8. Performance Characteristics of Drive Scheme with ANFIS- Speed controller (a) speed (rad/sec.) (b) current (amp.) (c) torque (Nm) (d) speed during loading cycle (e) speed ripples (f) torque ripples

V. CONCLUSION

A novel Neuro-fuzzy controller based vector controlled induction motor drive has been presented in this paper. Some of the advantages of ANFIS are reduced number of rules, faster speed of operation and no need for modifications in membership function by conventional trial and error method for optimal response. This makes NFC a easy-build and robust controller. The performances of the proposed NFC based drive have been investigated at various operating conditions. A performance comparison between PI based drive, FLC based drive and the proposed NFC based drive has been presented. The proposed NFC based IM drive has been found to be robust for high performance drive application.

Appendix A

The parameters of induction motor are as follows:

Nominal power (*P*):2.2KW; Voltage: 460V (L-L, rms); Phases: 3; Frequency: 60Hz; Stator resistance (R_s):1.77 ohms; Rotor resistance (R_r):1.34 ohms; Stator leakage reactance (X_{ls}):5.25 ohms; Rotor leakage reactance (X_{lr}):4.57 ohms; Mutual reactance (X_m):139 ohms; Rotor inertia (*J*): 0.025 Kg.m^2; Number of pole (*p*): 4.

Appendix B

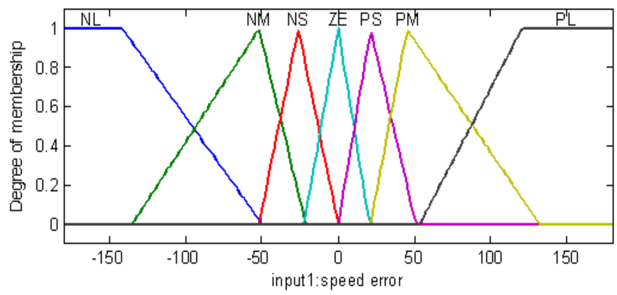
The design parameters of PI speed controller are as follows:

Proportional constant (K_p): 0.62445; Integral constant (K_i):0.01.

Appendix C

The design parameters of FLC speed controller are as follows:

Inputs to the FLC speed controller are speed error and rate of change of speed error and output is command current. Membership functions for input and output variables have been chosen with triangular shapes as shown in Fig. 9. Universe of discourse of input and output variables are divided in to seven fuzzy sets: NL (Negative Large), NM (Negative Medium), NS (Negative Small), ZE (Zero), PL (Positive Large), PM (Positive Medium), PS (Positive Small). Rule base for FLC speed controller is given in Table 4. Max-Product inference method and centroid defuzzification method are used.



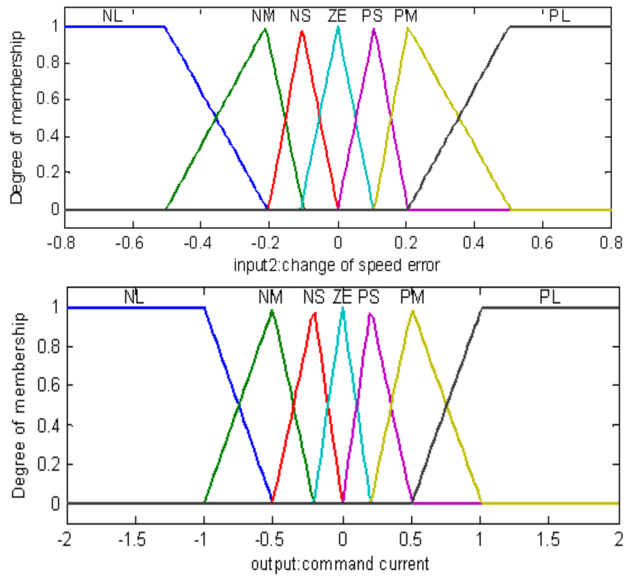


Fig. 9. Input and output membership function of FLC speed controller

Table 4: Rule base for FLC speed controller

cwe \ we	NL	NM	NS	ZE	PS	PM	PL
NL	NL	NL	NL	NL	NM	NS	ZE
NM	NL	NL	NL	NM	NS	ZE	PS
NS	NL	NL	NM	NS	ZE	PS	PM
ZE	NL	NM	NS	ZE	PS	PM	PL
PS	NM	NS	ZE	PS	PM	PL	PL
PM	NS	ZE	PS	PM	PL	PL	PL
PL	ZE	PS	PM	PL	PL	PL	PL

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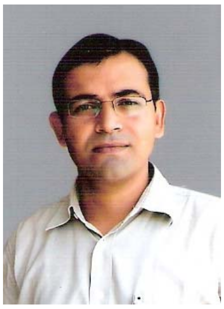
BIOGRAPHIES



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