Neuro Fuzzy Type-2 Based Space Vector Modulation for Inverter Fed Induction Motor Drive

Srinivas Gadde , G .Durga Sukumar

Abstract: In indirect vector control the conventional speed and current controllers operate satisfactory when the operating point is constant. But the operating point is always dynamic, the reference voltages obtained in a closed loop system feding to the inverter contains more harmonics. Due to this the pulses which are going to produce are uneven. Which intern produces the inverter output voltages which are more harmonics contained. In order to produce the better output voltage from the inverter, this paper presents neuro-fuzzy type-2 space vector modulation (NFT2) technique .A performance comparison of the inverter is done with conventional space vector modulation(SVM) and neuro fuzzy type- 1(NFT1) system using matlab simulation & experimental validation. The performance parameters of the induction motor based on current, torque and speed with neuro-fuzzy type-2 space vector modulation is compared with conventional and type-1neuro fuzzy SVM. The % THD of inverter output voltages are also compared .The experimental validation a dspace-1104 is used to analyze performance of induction motor which is obtained by the simulation. The experimental validations are carried out considering 2HP Induction motor in the lab

Keywords **:** ***Indirect vector control, Neuro Fuzzy type-2 controller (NFT2), Neuro Fuzzy type-1 Controller (NFT1),Space vector modulation (SVM), Induction motor (IM), Third harmonic distortion (THD).***

I. INTRODUCTION

Control techniques in the induction motor classified as into two types i.e Scalar control and vector control. Vector control method is frequently used in the induction motor to get better performance. The voltage source inverter generally depends on switching scheme from various pulse width modulation techniques. For better performance of minimization switching waveforms and flexibility use space vector modulation technique .The ANFIS network is does not depends on switching frequency and trained by using hybrid algorithm. Due to algorithm SVM (Space vector modulation) can be developed very fast with minimum number of iterations. [1].Duty ratios are generated for output, it depends on angle of space vector and change of angle in space vector. The performance of neuro-fuzzy SVM is compare with conventional SVM. The comparison is based on total harmonic distortion of inverter line to line voltages of neuro fuzzy based system with conventional SVM [2].Inverter control of Induction motor drive applied with concept of type-2 fuzzy logic with SVM method applied for voltage source inverter.The THD values obtained for inverter voltages at 15KHz frequencies [3]. Neuro fuzzy SVM based method is used to minimize the number of iterations and third harmonic distortion compared with conventional SVM due to hybrid learning algorithm [4].The SVM algorithm is developed by several subnets in structure of artificial neural network for two-level inverter. Due to this obtain improved performance the Induction motor [5].The simplicity SVM algorithm without flux controller and current transformations developed using direct flux vector control method [6]. The high power rating Induction motor drive ripple in torque is reduced using SVPWM method and also comparison of ripple conventional two level inverter with five level inverter [7].The induction motor performance is improved with type-2 neuro fuzzy sliding mode compare with Neuro fuzzy type-1 when control parameter changes [8].The clustering and gradient algorithm are used to developed the novel neuro fuzzy type-2 system [9]. Pulse width modulation with hybrid space to obtain three phase duty ratio is difficult at higher switching levels frequencies and require sector identification .Implementation of NFC is independent of switching frequency and duty ratio with rotation angle ,change of rotation of angle at higher switching level frequency [10].To reduce torque ripple with performance of induction motor type-2 fuzzy logic speed & current controller placed instead of convention PI speed & current controller .The induction drive implement at no load & step change in load and THD values are compared [11].Direct torque control of Induction motor drive with SVPWM method is used to reduced ripples in torque ,voltage and current[12].Type-2 FNN is compared with type-1 fuzzy systems [13].The comparison of performance between proportional integral (PIDTC) with F2DTC [14]. The ripple contents are reduced in stator current, flux and torque with proposed a technique fuzzy logic control based speed control loop [15].In section-II explains the Induction motor mathematical modeling and space vector modulation .section-III explains the two level inverter with mathematical modeling. .In section-IV explains the neuro fuzzy type-2 based space vector modulation. In section-VI explains the results and discussion compared with conventional SVM. In section-VI explains the conclusions.

II. INDUCTION MOTOR MATHEMATICAL MODELING

The stator voltage and flux equations are developed for 3-phase squirrel cage induction motor with mathematical modeling. Which are referred to a general reference frame is indicated by the superscript ‘g’ and following equation are shown as

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Stator flux:

$$\Psi_s^g = L_s i_s^g + L_m i_r^g = L_s \sigma i_s^g + \frac{L_m}{L_r}\Psi_r^g \quad (1)$$

Rotor flux :

$$\psi_r^g = L_r i_r^g + L_m i_s^g = L_s \sigma i_r^g + \frac{L_m}{L_r}\psi_s^g \quad (2)$$

Stator voltage :

$$U_{dqs}^g = R_r i_{ds}^g + \partial(L_s \sigma i_{dqs}^g + \frac{L_m}{L_r}\psi_{dqr}^g) + J\,\omega_A \psi_{dqs}^g \quad (3)$$

Rotor Voltage:

$$0 = R_r i_{dqr}^g + \partial \psi_{dr}^g - J(\omega_A - \omega_r)\psi_{dqs}^g \quad (4)$$

Mechanical equations:

$\tau_{e-}\tau_L = J_m \partial_{\omega r} + B_m \omega_r$ ....(5)

Electromagnetic Torque:

$$\tau_e = \frac{3}{2}\frac{P}{2}(\Psi_{ds}^g i_{qs}^g - \Psi_{qs}^g i_{ds}^g) \quad (6)$$

The above induction machine model equations are referring to a stationary frame .it is derived simply by substituting ω_A=0 in equations (3) and (4) and indicated by the superscript ‘Q’ .which is with d-axis attached on the stator phase ‘A’ winding. The machine model can be rewritten in a stationary frame as follows .

Stator flux:
$$\overline{\psi_s^Q} = L_s \sigma i_s^Q + \frac{L_m}{L_r}\overline{\psi_r^Q} \quad (7)$$

Rotor flux:
$$\overline{\psi_r^Q} = L_r \sigma i_r^Q + \frac{L_m}{L_r}\overline{\psi_s^Q} \quad (8)$$

Stator voltage: $\overline{U_{ds}^Q} = R_s i_{ds}^Q + \partial\left(L_s \sigma i_{ds}^Q + \frac{L_m}{L_r}\overline{\Psi_{dr}^Q}\right)$ (9)

$$\overline{U_{qs}^Q} = R_s i_{qs}^Q + \partial\left(L_s \sigma i_{qs}^Q + \frac{L_m}{L_r}\overline{\Psi_{qr}^Q}\right) \quad (10)$$

Rotor voltage : $0 = R_r i_{dr}^Q + \partial\overline{\Psi_{dr}^Q} + j\omega_r \overline{\Psi_{qr}^Q}$ (11)

$$0 = R_r i_{qr}^Q + \partial\overline{\Psi_{qr}^Q} - j\omega_r \overline{\Psi_{dr}^Q} \quad (12)$$

Mechanical equation: $\tau_e = J_m \partial\omega_r + B_m W_r + \tau_L$ (13)

Electro-magnetic Torque: $\tau_e = \frac{3}{2}\frac{P}{2}\left(\overline{\Psi_{ds}^Q} i_{qs}^Q - \overline{\Psi_{qs}^Q} i_{ds}^Q\right)$ (14)

$$\partial = \frac{d}{dt}$$

$$\sigma = 1 - \left(\frac{L_m}{L_s L_r}\right)$$

i_s, i_r -indicate the stator and rotor currents,

$\bar{\psi}_{ds}, \bar{\psi}_{dr}$ d-axis stator and rotor flux linkages

$\bar{\psi}_{qs}, \bar{\psi}_{qr}$ q-axis stator and rotor flux linkages

L_s, L_r stator and rotor flux linkages

L_m Mutual inductance

R_s, R_r Stator and rotor resistance

P is the number of poles

III. TWO-LEVEL INVETER WITH MATHEMATICAL MODELLING

Space vector is a technique is used to control the PWM (pulse width modulation) used in variable speed drives.

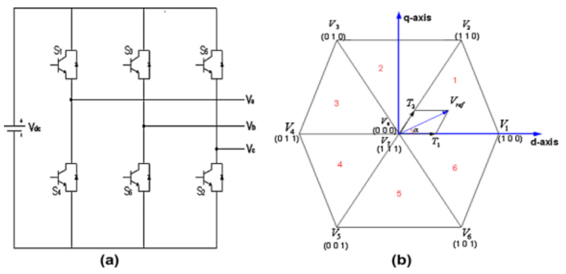


Fig.1.(a) two-level inverter (b) SV diagram with active vectors

The fig shown that the connection diagram of two-level inverter eight switching vectors with space vector rotation. These different vectors are used for switching states of two-level inverter. The resultant voltage is zero when V_0 and V_7 vectors are selected. The effective voltage is fed to induction machine by selecting remaining vectors are V_1 to V_6.

The reference voltage (V_{ref}) with a constant value is generated with at angle of α by using zero vectors (V_0 & V_7) in combination nearest two active vectors V_n,V_{n+1} .The effective vectors are used to obtain desired output by using two active vectors .

From above concept the mean voltage criteria, the reference vector in unit sampling time can be stated as

$V_{ref} = (T_1.V_n + T_2.V_{n+1})/T_s$ (15)

T_1,T_2 are represents the V_1-V_6 sectors active times.(15)

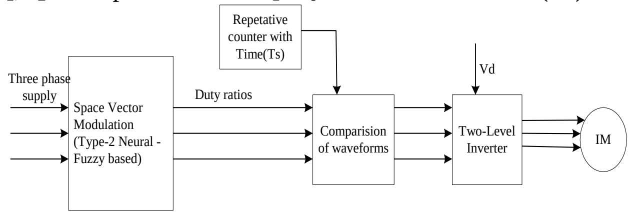


Fig.2 Proposed NFT2 based SVM for inverter control.

Along direct axis while equating the equations are

$$V_{ref}\cos\alpha.T_S = V_{dc}.T_1\left(V_{dc.}\cos\frac{\pi}{3}\right)T_2 \quad (16)$$

Along quadrature axis while equating the equations are

$$V_{ref}\sin\alpha.T_S = V_{dc}.T_1\left(V_{dc.}\sin\frac{\pi}{3}\right)T_2 \quad (17)$$

The starting vector is 60^0 with respective to V_{ref} at an angle of α & each active vector V_1-V_6 with constant magnitude value is V_{dc}

Where α is the angle of Vref in a 60^0 sector with respect to the beginning of the sector and Vdc is the magnitude of each active vector (V_1-V_6).

$$T_1 = M.\frac{Sin\left(\frac{\pi}{3}-\alpha\right)}{Sin\left(\frac{\pi}{3}\right)}.T_{s,} \quad (18)$$

$$T_2 = M.\frac{Sin(\alpha)}{Sin\left(\frac{\pi}{3}\right)}.T_{s,}, \quad (19)$$

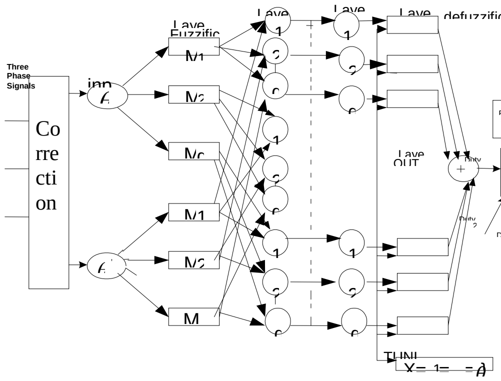
$$T_o = T_s - T_1 - T_2 \quad (20)$$

The duration of zero vector with sampling period represents time Ts ,M is represents modulation index i.e $M = \frac{V_{ref}}{Vdc}$

When time is equally distributed then ripple value is reduced to zero.

IV. NEURO FUZZY TYPE-2 BASED SVM

The IF-THEN rules are used to implement neuro-fuzzy type-2 system ,it invovles rules of antecedent and cossequent parts with type-2 fuzzy values.In Gaussian type-2 fuzzy sets uncertainties can be associated to the mean and the standard deviation.Gaussian type-2 fuzzy sets with uncertain standard deviation and uncertain mean are shown Structure of type-2 fuzzy neural system.



Layer-1 Input layer: This layer gives inputs to the fuzzification layer and in this layer connectas many no of nodes as the no of facial features m. the input layer of output given as

$u^t_i = x^t_{i(\theta)}$ $\quad$ i=1,2,3……..m $\qquad$ (20)

Layer-2 Fuzzification layer: each node calculates the membership of input data with the rule of antecedents by employing the interval type-2 gaussian membership function. The membership of i^th input feature with k^th rule is given by.

$$\emptyset^t_{ik(\theta)} = \exp\left(-\frac{(\mu^t_1-\mu_{1k(\theta)})^2}{2\sigma^2_{k(\theta)}}\right) = \emptyset(\mu_{ik(\theta),}\sigma_{k(\theta)},\mu^t_i) \qquad (21)$$

$$\emptyset^{lo}_{1k(\theta)} = -\exp\left(\frac{(\mu^t_1-\mu_{1k(\theta)})^2}{2\sigma^2_{k(\theta)}}\right)$$

$$\emptyset^{lo}_{2k(\theta)} = -\exp\left(\frac{(\mu^t_2-\mu_{2k(\theta)})^2}{2\sigma^2_{k(\theta)}}\right) \qquad (22)$$

$$\emptyset^{lo}_{k(\theta)} = -\left(\frac{(\mu^t_1-\mu_{1k(\theta)})^2+(\mu^t_2-\mu_{2k(\theta)})^2\ +\cdots+(\mu^t_n-\mu_{nk(\theta)})^2}{2\sigma^2_{k(\theta)}}\right) \qquad (23)$$

$$\emptyset^{up}_{k(\theta)} = -\left(\frac{(\mu_{1k(\theta)}-\mu^t_2)^2+(\mu_{2k(\theta)}-\mu^t_2)^2\ +\cdots+(\mu_{nk(\theta)}-\mu^t_n)^2}{2\sigma^2_{k(\theta)}} \qquad (24)$$

where, $\mu_{ik(\theta)} \in [{}^1\mu_{ik(\theta)}, {}^2\mu^t_i]$are the left and right limits of the center and σ_k is the width of k^th rule.

The footprint of uncertainty of this membership function can be represented as a bounded interval in terms of upper membership function $\emptyset^{up}$ and lower membership function $\emptyset^{lo,}$ as given below

$$\emptyset^{up,t}_{ik(\theta)} = \begin{cases} \emptyset(\ {}^1\mu_{ik(\theta)},\sigma_{k(\theta)},\mu^t_i & \mu^t_i <^1 \mu_{ik(\theta)} \\ ½ & {}^1\mu_{ik(\theta)} \le \mu^t_i \le^2 \mu_{ik(\theta)}.25 \\ \emptyset({}^2\mu_{ik(\theta)},\sigma_{k(\theta)},\mu^t_i & \mu^t_i >^2 \mu_{ik(\theta)} \end{cases} \qquad (25)$$

$$\emptyset^{lo,t}_{ik(\theta)} = \begin{cases} \emptyset({}^1\mu_{ik(\theta)},\sigma_{k(\theta)},\mu^t_i & \mu^t_i \le \frac{({}^1\mu_{ik(\theta)}+{}^2\mu_{ik(\theta)})}{2} \\ \emptyset({}^{2\mu_{ik(\theta)}},\sigma_{k(\theta)},\mu^t_i & \mu^t_i > \frac{({}^1\mu_{ik(\theta)}+{}^2\mu_{ik(\theta)})}{2} \end{cases} \qquad (26)$$

The output of each node can be represented by the interval

$$\emptyset^t_{ik(\theta)} = [\emptyset^{lo,t}_{ik(\theta)}, \emptyset^{up,t}_{ik(\theta)}] \qquad (27)$$

Layer 3- *Firing layer*: In this layer each node calculate the firing strength of a rule. It consists of 2×K nodes where K nodes represent upper and lower firing strength of K rule. Then the algebraic product of operation is applied the rule antecedent to calculate the firing strength of a rule and it is given by

$$[F^{lo,t}_{k(\theta)}, F^{up,t}_{k(\theta)}];\ k = 1,\ldots\ldots,K = min[F^{lo,t}_{k(\theta)}, F^{up,t}_{k(\theta)}]; \qquad (28)$$

Substitute the above equation

$$F^t_{k(\theta)} = \sum_{i=1}^m \frac{1}{2\sigma^2_{k(\theta)}}\left[(\mu^t_i - \mu_{ik(\theta)})^2, (\mu_{ik(\theta)} - \mu^t_i)^2\right] \ (29)$$

Layer 4- *Type reduction layer*: This layer consists of K nodes .In this layer each nodes performs type reduction of interval type-1 fuzzy set to a fuzzy number for these type reduction employed a variant of Nie-Tan type-reduction . This approach is closed form approximation of well-known Karnik-Mendel algorithm. The output of each node is given as

$$F^t_{k(\theta)} = \alpha F^{lo,t}_{k(\theta)} + (1-\alpha)F^{\mu p,t}_{k(\theta)};\quad k = 1\ldots\ldots\ldots..K \qquad (30)$$

$$F^t_{k(\theta)} =$$

$$\alpha\left[-\left(\frac{(\mu^t_1-\mu_{1k(\theta)})^2)}{2\sigma^2_{k(\theta)}}\right)\sum_{i=1}^m +(1-\alpha)\sum_{i=1}^m \frac{1}{2\sigma^2_{k(\theta)}}(\mu_{ik(\theta)} - \right.$$

$\mu it)2]$ (30)

$$F^t_{k(\theta)} = 1 - \alpha\left[\sum_{i=1}^m \frac{(\mu^t_i-\mu_{ik(\theta)})^2+(\mu_{ik(\theta)}-\mu^t_i)^2}{2\sigma^2_{k(\theta)}}\right] \qquad (31)$$

where α is the weighted measure of uncertainty and is set as 0.5.

Layer 5: *Normalization layer*: This layer consists of K nodes and each node normalizes the firing strengths of rule that is generated by the type reduction layer:

$$\overline{F^t_{k(\theta)}} = \frac{F^t_{k(\theta)}}{\sum_{p=1}^K F^t_{k(\theta)}};\quad k = 1,\ldots\ldots..K \qquad (32)$$

Layer 6 : Output layer: This layer computes the output of the network by the normalized weighted sum of firing strengths of rules and is given as:

$$\widetilde{y^t_j} = \frac{\sum_{k=1}^K w_{kj} F^t_k}{\sum_{p=1}^K F^t_p}; j = 1,2,\ldots\ldots.,n \qquad (33)$$

$$\widetilde{y_j^t}=\frac{\sum_{k=1}^{K} w_{kj}\left[1-\alpha\left[\sum_{i=1}^{m}\frac{(\mu_i^t-\mu_{ik(\theta)})^2+(\mu_{ik(\theta)}-\mu_i^t)^2}{2\sigma_k^2}\right]\right]}{\sum_{p=1}^{K}F_p^t} \qquad (34)$$

Where, w_{kj} is the output weight connecting k^{th} rule with the j^{th} output node.

Learning Algorithm

To calcucate the weights of network applied with learning algorithm used as regularised form of project based learning algorithum.To find the minimum weight of network with reduced hinge error proposed as project based leaning algorithm. however, minimizing only the hinge-error may lead to over fitting. Hence, in this prosposed work the sum of squared hinge-error is regularized for all samples with a regularizing factor.

The hinge-error is defined as

$$J_t=\sum_{j=1}^{n}\begin{cases}\left(\widetilde{y_j^t}-\sum_{k=1}^{k} w_{kj}\,F_k^t\right)^2 if\ \widetilde{y_j^t}<1\\ 0, \qquad\qquad othwrwise\end{cases} \qquad (35)$$

where,

$$\overline{F_{k(\theta)}^t}=\frac{F_k^t}{\sum_{p=1}^{K}F_k^t} \qquad k=1,\ldots.,K \qquad (36)$$

$$\overline{F_{k(\theta)}^t}=\frac{1-\alpha\left[\sum_{i=1}^{m}\frac{(\mu_i^t-\mu_{ik(\theta)})^2+(\mu_{ik(\theta)}-\mu_i^t)^2}{2\sigma_{k(\theta)}^2}\right]}{\sum_{p=1}^{K}F_p^t} \qquad (37)$$

$$J_t=\sum_{j=1}^{n}\left[\frac{\sum_{k=1}^{k} w_{kj}F_k^t}{\sum_{p=1}^{K}F_p^t}-\sum_{k=1}^{k} w_{kj}F_k^t\right] \qquad (38)$$

$$J_t=\sum_{j=1}^{n}\left\{\frac{\sum_{k=1}^{k} w_{kj}[1-\alpha\left[\sum_{i=1}^{m}\frac{(\mu_i^t-\mu_{ik(\theta)})^2+(\mu_{ik(\theta)}-\mu_i^t)^2}{2\sigma_{k(\theta)}^2}\right]}{\sum_{p=1}^{K}F_p^t}\right. \qquad (39)$$

The Amalgamation Of Mean Least Squares Optimization (Lse) And Gradient Descent Back Propagation Algorithms Gives Rise As Well As Tuning To The Fuzzy Model. An Error Measure Is Reduced By Adding The Squared Difference Between Actual And Desired Output. Obtaining Of Error Rate Or The Pre-Determined Epoch Number Prevents The Training. The Non-Linear Premise Parameters Are Fine-Tuned By Implementing The Gradient Descent Algorithm On The Other Hand To Minimize The Linear Consequent Parameters Theme An Least-Square Is Used Forward Pass As Well As Backward Pass is Composed In The Learning Algorithm At Each Period

Forward Pass

In the forward pass, each node output is calculated in NFT2 controller by training set of input patterns space vector angle (θ) and change in space vector angle (θ') and Least-Squares estimator is used to identify the rule linear consequent parameters. The duty ratio or output vector is a linear function in the Takagi-sugeno model. The Gaussian membership function enriched with three parameters a, b, &c training set of input (Error and change in error) - output (duty ratio) patterns are linear equations , $(m_{1j}, n_{j,}\ and\ r_i)$ as

$$D_{1-p}=\overline{\omega_1}(1)f_1(1)+\overline{\omega_1}(1)f_2(1)+\cdots\overline{\omega_n}(1)f_n(1) \quad (40)$$

$$D_{1-p}=\overline{\omega_1}(2)f_1(2)+\overline{\omega_1}(2)f_2(2)+\cdots\overline{\omega_n}(2)f_n(2) \quad (41)$$

$$D_{1-p}=\overline{\omega_1}(m)f_1(m)+\overline{\omega_1}(m)f_2(m)+\cdots\overline{\omega_n}(m)f_n(m) \quad .(42)$$

$$\begin{aligned}D_1(1)=&\ \overline{\omega_1}(1)[p_1\theta(1)+q_1\theta(1)+r_1]\\&\overline{\omega_2}(1)[p_2\theta(1)+q_2\theta(1)+r_2]+\cdots+\\&\overline{\omega_n}(1)[p_n\theta(1)+q_n\theta(1)+r_n]\ldots\end{aligned} \qquad (43)$$

.

$$\begin{aligned}D_1(2)=&\ \overline{\omega_1}(2)[p_1\theta(2)+q_1\theta(2)+r_1]\\&\overline{\omega_2}(2)[p_2\theta(2)+q_2\theta(2)+r_2]+\cdots+\\&\overline{\omega_n}(2)[p_n\theta(2)+q_n\theta(2)+r_n]\end{aligned} \qquad (44)$$

$$\begin{aligned}D_1(m)=&\ \overline{\omega_1}(m)[p_1\theta(m)+q_1\theta(m)+r_1]\\&\overline{\omega_2}(m)[p_2\theta(m)+q_2\theta(m)+r_2]+\cdots+\\&\overline{\omega_n}(m)[p_n\theta(m)+q_n\theta(m)+r_n]\end{aligned} \qquad (45)$$

Where N represents the input-output patterns, In the rule layer (=25) n represents numberof nodes ,D_{1-N} is the expected duty ratio of the NFT2.

The above Equation(44)represented as follows

$$D_{1-p}=Ak \qquad (46)$$

where $D_{1-N}$is an m×1=10,000×1

$$D_{1-p}=\begin{bmatrix}D_{1-p(1)}\\D_{1-p(2)}\\ .\\ .\\ .\\D_{1-p(m)}\end{bmatrix} \qquad (47)$$

$$A=\begin{bmatrix}\varpi_1(1) & \varpi_1\theta(1) & \varpi_1\theta'(1) & . & . & \varpi(1) & \varpi_n(1)\theta(1) & \varpi_n\theta'(1)\\ \varpi_1(2) & \varpi_1\theta(2) & \varpi_1\theta'(2) & . & . & \varpi(2) & \varpi_n(2)\theta(2) & \varpi_n\theta'(2)\\ . & . & . & . & . & . & . & .\\ . & . & . & . & . & . & . & .\\ \varpi_1(m) & \varpi_1\theta(m) & \varpi_1\theta'(m) & . & . & \varpi(m) & \varpi_n(m)\theta(m) & \varpi_n\theta'(m)\end{bmatrix} \quad (48)$$

A can be represented by $M\ x\ X$ (1+number of inputs parameters=10,000x75 matrix,

And Y is an X (1+ input variables x 1) x1=75 x1 vector unidentified consequent parameters as

$$k=[m_1n_1r_{1,}m_2n_2r_2\ldots\ldots.m_nn_nr_n]^T \quad (49)$$

In the above case, in training 10,000 input–output patterns are used which gives complexity, so the solution may not exist to the Eq. (48). As an alternative, least squared estimate of K should be identified to find out the exact solution with minimizing squared error as: $Ak-D_{1-N}^2$

By using the pseudo-inverse technique, the least-squares estimate is achieved which is as follows

$$k^*=(A^T\ A)^{-1}\ A^T\ D_{1-m}. \qquad (50)$$

Where $(A^TA)^1\ A^T$ is the pseudo inverse of A. After the establishment of consequent parameters, the error vector e and output vector D_1 can be calculated a

$$e=D_{1-N}-D_1 \qquad (51)$$

Backward Pass

The back propagation algorithm is used in the backward pass. By using chain rule ,the antecedent parameters are updated and error signals are propagated. The chain rule can be represented in equation form as

$$\Delta a = -\eta \frac{\partial E}{\partial a} = -\eta \frac{\partial E}{\partial e} \times \frac{\partial e}{\partial D_1} \times \frac{\partial D_1}{\partial (\varpi f_i)} \times \frac{\partial (\varpi f_i)}{\partial \varpi_i} \times \frac{\partial \varpi_i}{\partial \omega_i} \times \frac{\partial \omega_i}{\partial \omega_{Ai}} \times \frac{\partial \omega_{Ai}}{\partial a}, \quad 52$$

$$E = \frac{1}{2} e^2 = \frac{1}{2}(D1 - P - D1), \quad (53)$$

$$\Delta a = -\eta (D_{1-P} - D_1)(-1) f_i \times \frac{\varpi_i (1-\varpi_i)}{\omega_i} \times \frac{\omega_i}{\omega_{Ai}} \times \frac{\partial \omega_{Ai}}{\partial a},$$

Where

$$\frac{\partial \omega Ai}{\partial a} = \frac{1}{\left[1+\left(\frac{\theta - a}{c}\right)^{2b}\right]^2} \times \frac{1}{c^{2b}} \times 2b \times (\theta - a)^{2b-1} \times (-1)$$

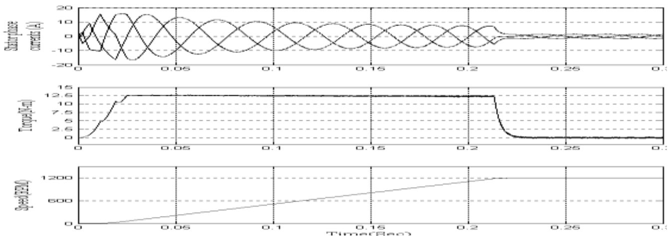
$$= \omega_{Ai}^{2} \times \frac{2b}{c} \times \left(\frac{\theta - a}{c}\right)^{2b-1}. \quad 54$$

Similarly, the parameters b and c can be determined by applying corrections

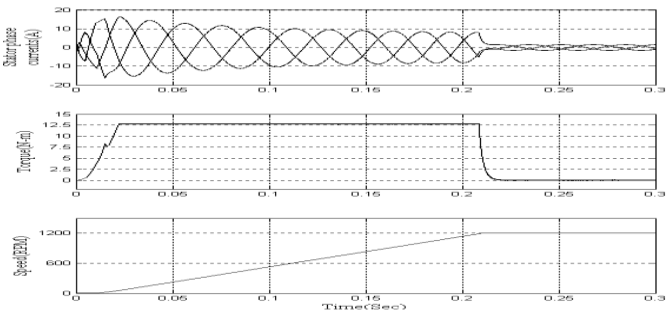
V. RESULTS AND DISCUSSIONS

The observe response of Induction motor with PI,NFT1C and NFT2C controller and reference speed of Induction motor is 1200 rpm.

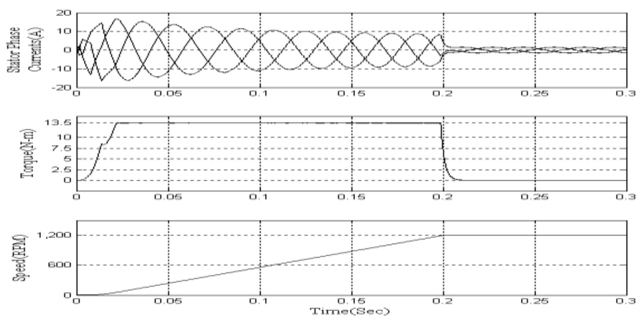
a) During Starting



(a) Conventional SVM



(b) Neuro fuzzy type-1 based SVM

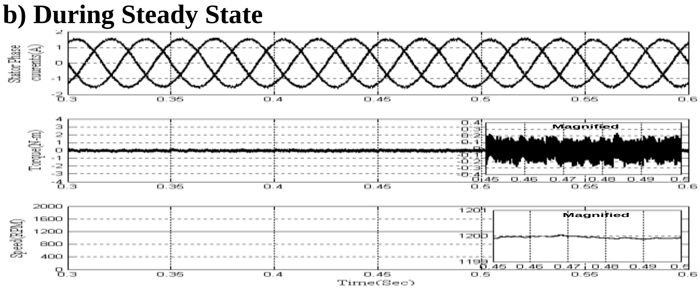


(c) Neruo fuzzy type-2 based SVM

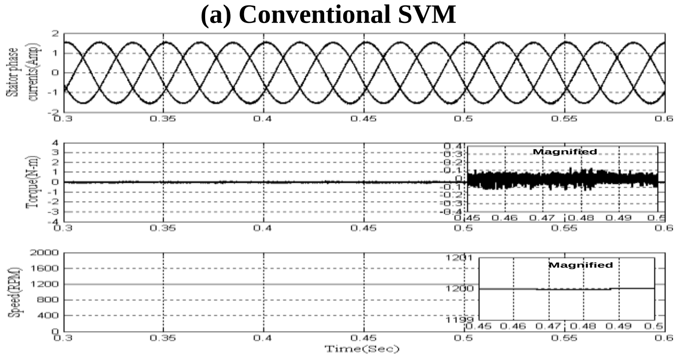
Fig.5.2 : Performance of Induction motor during starting

The speed response of Induction motor during starting reached early in NFT2 controllers compared to conventional and NFT1 controllers SVM based controller within time interval between 0.2 to0.25sec and ripple in torque is reduced in NFT2 compared to conventional and NFT1 based SVM control method.

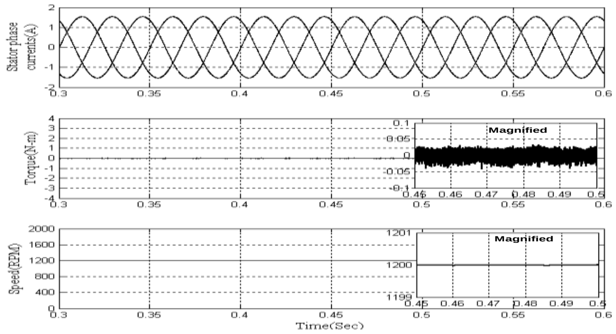
b) During Steady State



(a) Conventional SVM



(b) Neuro fuzzy type-1 based SVM

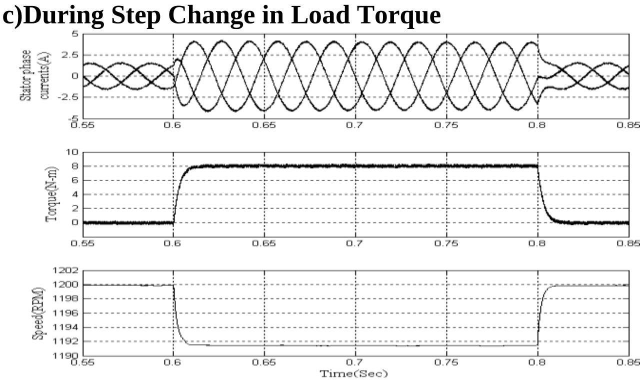


(c) Neuro fuzzy type-2 based SVM

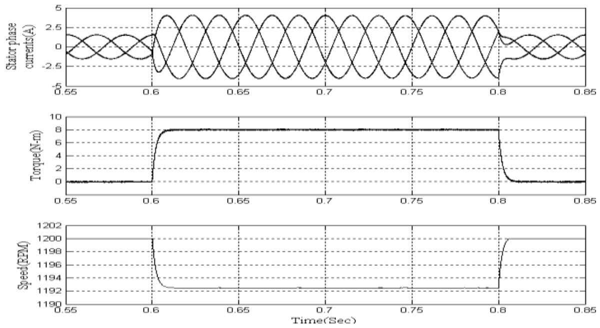
Fig. 5.3: Performance of Induction motor during steady state

The response of induction during steady state ,the ripple in torque is reduced with NFT2 controller compared with conventional and NFT1 controller .The speed response of Induction motor is magnified within interval of time 0.5sec to 0.6 sec compared to conventional and NFT1 based controller.

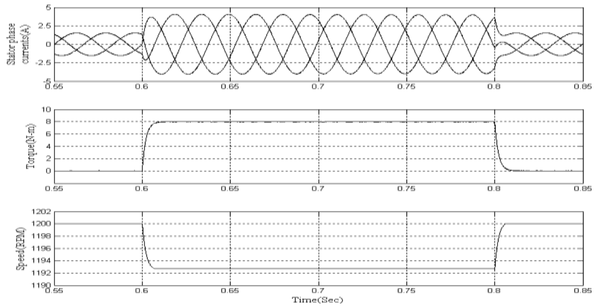
c)During Step Change in Load Torque



(a) Conventional SVM



(b)Type-1 Neuro fuzzy based SVM

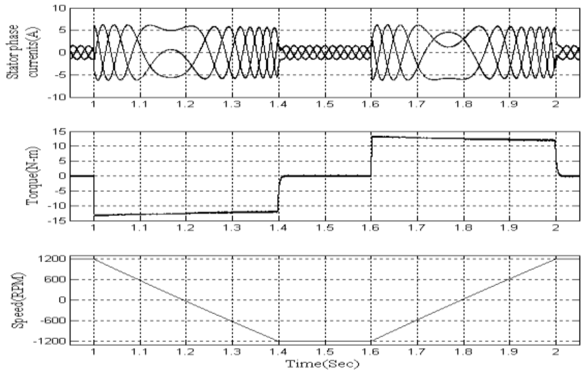


(c) Neuro fuzzy type-2 based SVM

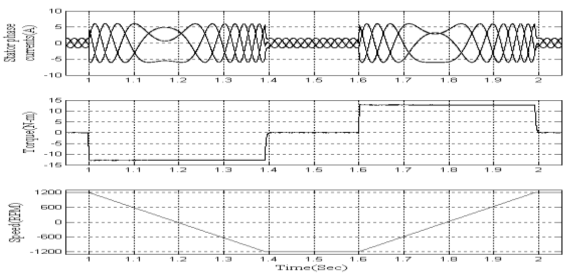
Fig. 5.4: Performance of Induction motor during step change in load torque

The ripple in torque during step change in load torque is reduced in NFT2 controller compared with conventional and NFT1 SVM controller based. The speed response also increased in NFT2 compared with conventional and NFT1 controller.

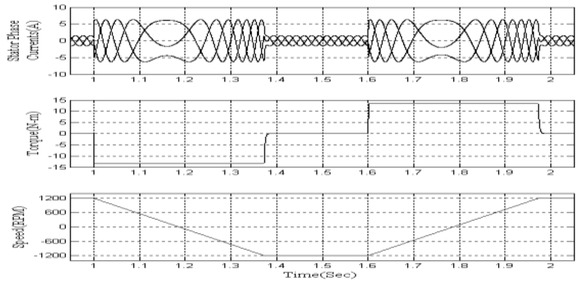
d) During Speed Reversal



(a) Conventional SVM



(b) Neuro fuzzy type-1 based SVM



(c) Neuro fuzzy type-2 based SVM

Fig. 5.5: Performance during speed reversal operation (from +1200 rpm to -1200 rpm and from -1200 to +1200)

The ripple in torque and stator current during speed reversal is reduced in NFT2 controller compared with conventional and NFT1 SVM controller based. The speed response also increased in NFT2 compared with conventional and NFT1 controller.

e) Experimental Validation

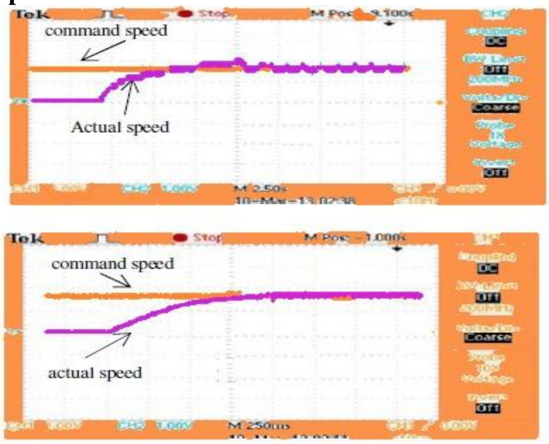
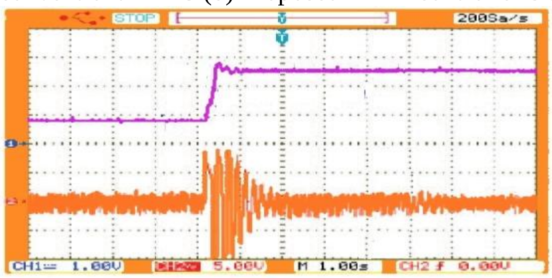
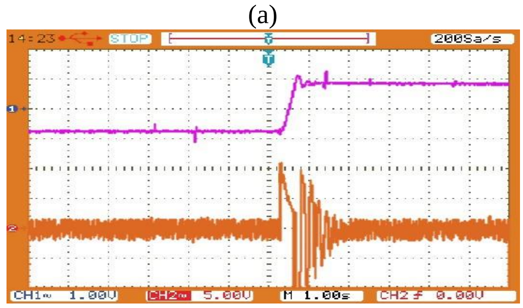


Fig 5.6 Experimental Speed responses of the IM drive for command speed of 125.6 rad/s

(a) conventional DTC (b) Proposed NFT2 controller SVM



(a)



(b)

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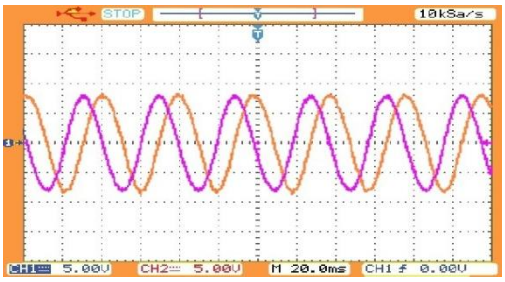

(c)

Fig 5.7 Experimental response (a) Actual speed and torque in forward motoring (b) Actual speed and torque in reverse and forward motoring(brown –torque and 1Div=5N-m)(blue-speed and 1Div=10rad/sec) (c) direct axis & quadrature axis flux at 125.6 rad/sec (1Div=0.5wb)

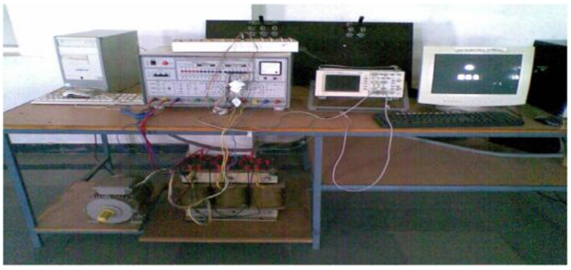

Fig 5.8 Experimental setup.

CONCLUSIONS

The dynamic performance of Induction motor drive is improved with proposed NFT2 controller as compared with conventional DTC .The ripple in torque and stator current is reduced in proposed NFT2 controller as compared with conventional DTC and NFT1 controlled based SVM.The torque is 8% increased in NFT2 controller compared with conventional DTC and NFT1 based SVM during starting. The ripple in torque 87.5% is reduced in NFT2 controller compared with conventional DTC and NFT1 based SVM within time interval 0.5sec to 0.6sec .The speed response is smooth and also magnified within time interval 0.5sec to 0.6sec in NFT2 compared with conventional DTC and NFT1 during steady state .when step change in load torque is applied to drive the ripple in torque and speed is reduced in NFT2 compared with conventional SVM and NFT1 controller SVM. The speed response reaches fastest during speed reversal condition in NFT2 compared with conventional SVM and NFT1 controller SVM.

The Experimental results are validation with matlab simulation results. The dspace (ds1104)is used to implement the real time simulation of controller modeled in the simulink.The NFT2 controller scheme uses learning algorithm trained data .In experimental results the speed response reaches smoothly without any ripple in NFT2 controller compared with conventional DTC shown in fig 5.6.During speed reversal and forward condition of drive shown in fig 5.7(a&b) ,torque ripple is reduced and fastest speed responses is attained .In fig 5.7(c) shown d-axis and q-axis flux withot ant ripple.

Using NFT2 controller fastest and dynamic responses are obtained compared with conventional DTC and NFT1 controller.

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