Indirect Vector Control of Induction Motor using ANN Estimator and ANFIS Controller

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ABSTRACT

This paper proposes the neural network solution to the indirect vector control of three phase induction motor including an adaptive neuro fuzzy controller. The basic equations and elements of the indirect vector control scheme are given. The proposed control scheme is realized by an adaptive neuro-fuzzy controller and two feed forward neural network. The neuro-fuzzy controller incorporates fuzzy logic algorithm with 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. The two feed forward neural network are used as estimator, learned by the Levenberg-Marquardit algorithm with data taken from PI control simulations. The performance of proposed scheme is investigated at different load and speed conditions. The result of the proposed scheme are compared with PI controller. The simulation study indicates the 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, PI controller, Fuzzy logic controller(FLC),

1. INTRODUCTION

Three phase induction motors are widely used in the industrial world because they are economical and immune to heavy overloads. However the use of induction motor has its disadvantages, mainly the controllability, due to its complex mathematical model and its non-linear behaviour [2]. The vector control or field oriented control (FOC) theory is the base of a special control method for induction motor drives. With this theory induction motor can be controlled like a separately excited dc motor.This method enables the control of field and torque of the induction machine independently (decoupling) by manipulating the corresponding field oriented quantities. There exist two methods for PWM current controlled inverter - direct and indirect vector control [16, 2, 8] . This paper will consider the indirect control method, where the slip angle, the direct and quadrature axes stator current set point components in synchronous reference frame are computed from the torque and rotor flux set points and used for vector control.There are several papers of neural network application for indirect vector control drive. In [3] a feed forward neural network and back propagation learning are used for angular velocity estimation and control of induction motor using only stator current measurement. The paper [7] present a method of neural network velocity estimation and induction motor control based on flux, voltage, and current models. In [14] a neural controller is implemented based on TMS320C30 microprocessor in order to emulate an indirect vector control of an induction motor drive. There are several papers of fuzzy logic application for indirect vector controlled induction motor drives. In [11] a fuzzy learning enhanced speed control of an indirect vector control of induction motor drive is proposed. In [12] the performance of fuzzy logic controller has been investigated and compared with the conventional PI controller at different operating conditions. The paper [6] proposes a model reference adaptive scheme in which the adaption mechanism is executed using a PI controller and fuzzy logic. In paper [15] a complete vector control scheme of induction motor incorporating the fuzzy logic controller has been successfully implemented in real time using digital signal processor controller board DS1102. A proportional-integral and fuzzy logic speed controllers operating in indirect field orientation [13] are designed and compared under no load and various load conditions with different reference speeds.

Fuzzy Logic control (FLC) has proven effective for complex, non linear and imprecisely defined processes for which standard model based control techniques are impractical or impossible [9, 10] . Fuzzy Logic, deals with problems that have vagueness, uncertainty and use membership functions with values varying between 0 and 1 [9, 10]. It means if the data available is not reliable, or if the system is too complex to derive the required decision rules, then the development of a fuzzy logic controller become quite difficult.In this case, the expert knowledge can be used for framing the proper rules which can be further used to tune the controller for obtaining the better result. Artificial Neural Network (ANN) has the powerful capability for learning, adaptation, robustness and rapidity. Therefore the advantages of ANN has been used for framing the proper rules of the fuzzy logic controller by adaptation and learning algorithm which is called ANFIS controller. This paper presents a scheme of Indirect vector control of Induction motor with ANN estimator and an ANFIS controller for improving the transient response, when it is subjected to torque disturbances. The required data for training the ANN estimator and ANFIS controller is obtained by simulation of the closed loop system with PI controller.

2. MODELLING

2.1 Induction motor modelling

The mathematical model of a three phase squirrel cage induction motor in synchronous rotating reference frames is given by the following equations [16, 2, 8]

$$V_{ds}^{e} = R_s i_{ds}^{e} + p\lambda_{ds}^{e} - w_e\lambda_{qs}^{e} \quad (1)$$
$$V_{qs}^{e} = R_s i_{qs}^{e} + p\lambda_{qs}^{e} + w_e\lambda_{ds}^{e} \quad (2)$$
$$0 = R_r i_{dr}^{e} + p\lambda_{dr}^{e} - (\omega_e - \omega_r)\lambda_{qr}^{p} \quad (3)$$
$$0 = R_r i_{qr}^{e} + p\lambda_{qr}^{e} + (\omega_e - \omega_r)\lambda_{dr}^{e} \quad (4)$$

Where

$$\lambda_{ds}^{e} = L_s ids^{e} + L_m idr^{e} \quad (5)$$
$$\lambda_{qs}^{e} = L_s iqs^{e} + L_m iqr^{e} \quad (6)$$
$$\lambda_{dr}^{e} = L_r idr^{e} + L_m ids^{e} \quad (7)$$
$$\lambda_{qr}^{e} = L_r iqr^{e} + L_m iqs^{e} \quad (8)$$

and electromagnetic torque

$$T_e = \frac{3}{2}\frac{P}{2} L_m (i_{qs}^{e} i_{dr}^{e} - i_{ds}^{e} i_{qr}^{e}) \quad (9)$$
$$\omega_r = \frac{d\theta_r}{dt} \quad (10)$$
$$T_e = j_m \frac{d\omega_r}{dt} + B_m\omega_r + T_l \quad (11)$$

2.2 Indirect Vector Control

The indirect vector control is a technique that controls the dynamic speed of Induction motor.Unlike direct vector control, in indirect vector control, the unit vectors are generated in an indirect manner. Figure(1) explains the fundamental principle of

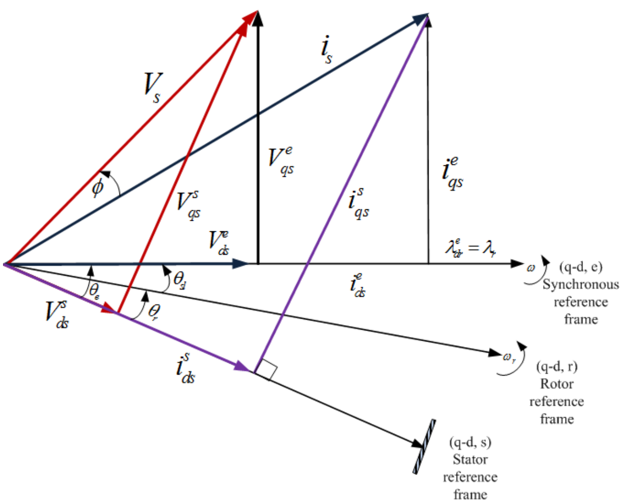

Fig. 1. Phasor diagram of Indirect vector control principle

indirect vector control with the help of phasor diagram. The d^s-q^s axes are fixed on the stator and d^r-q^r axes are fixed on the rotor which rotate at a speed ω_r . Synchronously rotating axes d^e-q^e are rotating ahead of d^r-q^r axes by the positive slip angle θ_{sl} corresponding to slip frequency ω_{sl}. Thus

$$\theta_e = \int \omega_e dt = \int (\omega_r + \omega_{sl})dt \quad (12)$$

For decoupling control $\lambda_{qr} = 0$ or $p\lambda_{qr} = 0$ and $\lambda_r = \lambda_{dr}$. Substituting the above condition in (3), (4), (7) and (8)

$$\omega_{sl} = \frac{R_r L_m i_{qs}^{e}}{L_r \lambda_r} \quad (13)$$
$$T_e = \frac{3}{2}\frac{P}{2}\frac{L_m}{L_r}\lambda_r i_{qs}^{e} \quad (14)$$
$$i_{qs}^{e} = \frac{2}{3}\frac{2}{P}\frac{L_r}{L_m}\frac{T_e}{\lambda_r} \quad (15)$$
$$i_{ds}^{e} = \frac{1}{L_m}[\lambda_r + \frac{L_r}{R_r}p\lambda_r] \quad (16)$$

3. STATOR CURRENT SET POINT ESTIMATION

The equations (13 - 16) are necessary and sufficient condition to produce an adequate field orientation. This conditions could be propagated to the set point variables.

$$\omega_{sl}^{*} = \frac{R_r L_m i_{qs}^{e^*}}{L_r \lambda_r^{*}} \quad (17)$$
$$i_{qs}^{e^*} = \frac{2}{3}\frac{2}{P}\frac{L_r}{L_m}\frac{T_e^{*}}{\lambda_r^{*}} \quad (18)$$
$$i_{ds}^{e^*} = \frac{1}{L_m}[\lambda_r^{*} + \frac{L_r}{R_r}p\lambda_r^{*}] \quad (19)$$

If we accept that the rotor flux set point is constant and its derivative is zero, the above equation is simplified as

$$i_{ds}^{e^*} = \frac{\lambda_r^{*}}{L_m} \quad (20)$$

Using the above equations a general block diagram of indirect vector control of induction motor drive is as shown in figure(2). It contains three principal blocks. They are

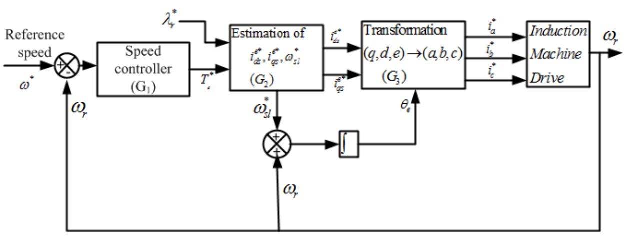

Fig. 2. General block diagram of indirect vector control of Induction motor

$G_1 \rightarrow$ Block of speed controller
$G_2 \rightarrow$ Block of estimation of $i_{ds}^{e^*}$, $i_{qs}^{e^*}$ and ω_{sl}^{*}
$G_3 \rightarrow$ Block of current co-ordinate transformation (q, d, e) to (a, b, c)

4. PROPOSED SCHEME

4.1 Block of speed controller

The speed controller block G_1 is proposed to be a neuro-fuzzy controller (ANFIS) which incorporate fuzzy logic algorithm with a five layer artificial neural network structure [1, 4] . The number and shape of each membership function related to the input variables can be obtained in an optimized way from data sets of inputs and output associated with a training algorithm.
The speed error and the rate of change of actual speed error are the inputs of the neuro-fuzzy controller which are given by

$$Input_1 = \varepsilon_\omega = \omega^{*} - \omega \quad (21)$$
$$Input_2 = \Delta\varepsilon_\omega = \varepsilon_\omega(n) - \varepsilon_\omega(n-1) \quad (22)$$

Where ω^* is the command speed.
First order Sugeno fuzzy model with five layer ANN structure [5] is used in proposed controller. In this five layer ANN structure the first layer represents inputs, the second layer represents fuzzification, the third and fourth layer represent fuzzy rule evaluations and the fifth layer represents de fuzzification. A two input first order Sugeno fuzzy model with two rules is depicted in figure(3).

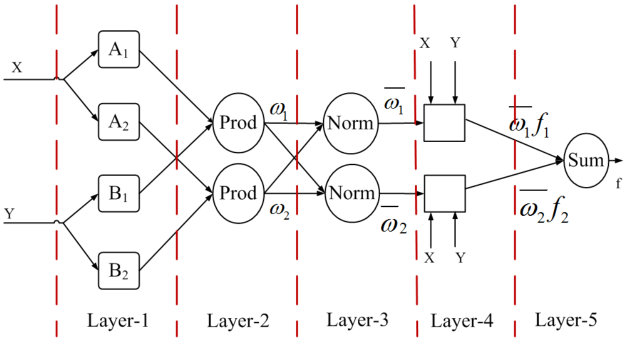

Fig. 3. ANFIS architecture of 2-input Sugeno fuzzy model with 2 rules.

Layer 1.

Every node i in this layer is an adaptive node with node function

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

$$O_{1i} = \mu_{Bi-2}(x) for i = 3,4 \tag{23}$$

where x(or y) is the input node i and A_i or B_{i-2} is a linguistic label associated with this node. Therefore O_{1i} is the membership grade of a fuzzy set (A_1, A_2, B_1, B_2). In the proposed scheme generalized bell function is used as membership function given by

$$\mu_A(x) = \frac{1}{1 + |\frac{x-c_i}{a_i}|^{2bi}} \tag{24}$$

where a_i, b_i, c_i are premise parameter set.

Layer 2.

Each node in this layer is a fixed node labelled prod whose output is the product of all incoming signals.

$$O_{2i} = w_i = \mu_{Ai}(x).\mu_{Bi}(y), i = 1,2 \tag{25}$$

Each node output represents the firing strength of a rule.

Layer 3.

Each node in this layer is a fixed node labelled Norm whose outputs are normalized firing strength given by

$$O_{3i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, i = 1,2 \tag{26}$$

Layer 4.

Every node in this layer is an adaptive node with a node function given by

$$O_{4i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{27}$$

where $\overline{w_i}$ is normalized firing strength from layer 3 and (p_i, q_i, r_i) is the consequent parameter set of this node.

Layer 5.

A single fixed node is in this layer labelled Sum which computes the overal output as the summation of incoming signals.

$$O_{5i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{28}$$

Hybrid learning algorithm is used in proposed controller [5]. It has two passes, forward pass and backward pass. In the forward pass of hybrid learning algorithm, node output goes forward until layer 4 and the consequent parameters are identified by the sequential least square method. In backward pass, the error signal propagates backward and premise parameters are updated by gradient descent that is back propagation learning method.

4.2 Block of estimation of i^{e*}_{ds}, i^{e*}_{qs} and ω^*_{sl}

The block G_2 for the estimation of i^*_{ds}, i^*_{qs} and w^*_{sl} is realized by a feed forward neural network. The topology of the multi layer feed forward network is of two inputs (flux and torque set points), three out puts (i^*_{ds}, i^*_{qs} and w^*_{sl}) and five and two neurons in the hidden layers (2-5-2-3). The off line algorithm of its learning is Levenberg-Marquardt. The final value of mean square error reached during the learning is 10^{-10}.

4.3 Block of current co-ordinate transformation

The block G_3 is realized by a feed forward neural network which performs a stator current set points (q-d,e) to (a,b,c) transformations. The topology of this multilayer feed forward network is of four inputs ($i^*_{ds}, i^*_{qs}, \sin\theta_e, \cos\theta_e$), three outputs ($i^*_{as}, i^*_{bs}, i^*_{cs}$) and two hidden layers of 20 and 10 neurons each (4-20-10-3). The off line algorithm of its learning is Levenberg-Marquardt. The final value of mean square error reached during the learning is 10^{-10}.

5. PERFORMANCE ASSESSMENT OF THE PROPOSED SCHEME

A complete simulation model for vector controlled Induction motor drive incorporating the proposed scheme is developed. It is simulated with PI controller and required data for training the ANFIS controller is obtained. The ANFIS controller is designed with two inputs, the speed deviation and its derivative and one control output. Seven linguistic variables for each input variable were used to get the desired performance. ANFIS uses neural networks to tune a fuzzy logic Sugeno type controller. To obtain the membership functions and the rules it presents hybrid learning with back propagation algorithm to tune them and least square methods to identify them. This paper uses the MATLAB ANFIS editor toolbox to train the ANFIS. The ANFIS inputs are used with seven generalized bell type membership functions, looking for a linear membership function at the output with an error tolerance equal to zero.

The membership functions before training and after training are shown in figure (5) and figure (6) respectively. To assess the proposed scheme, various simulation tests are carried out with PI controller and proposed scheme with ANFIS controller. The motor parameters are in Table1

Figure (7 and 8) shows the speed tracking performance of the motor following a trapezoidal speed reference with PI and ANFIS controller respectively. The speed tracking experiment is on no load condition.The speed error result shows that the proposed scheme is better than with PI controller. But it contains

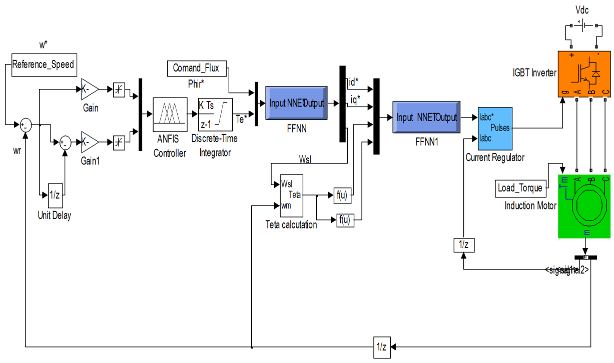

Fig. 4. Simulink model

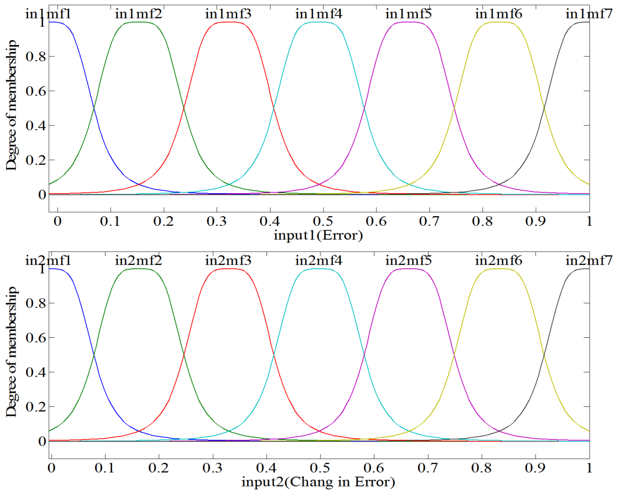

Fig. 5. Membership functions generated before training

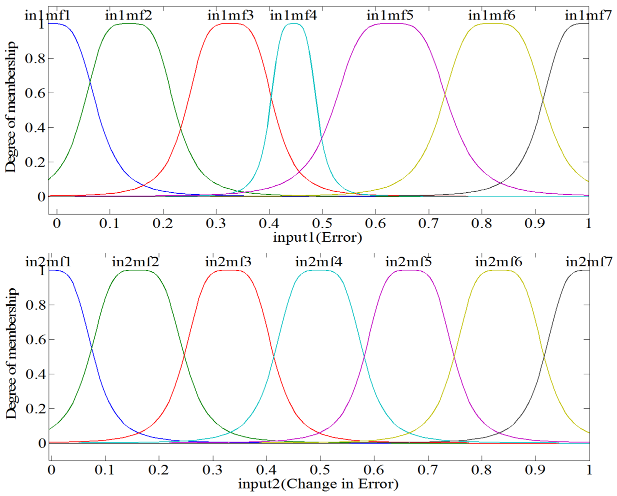

Fig. 6. Membership functions generated after training

ripple in torque at the time of speed change.

Figure (9 and 10) shows the load disturbance rejection capabilities of both the controllers, when the the load torque is suddenly changed from 25 Nm to 150 Nm. There is a considerable speed over shoot and speed dip(when the load torque rises) with PI controller as compared to proposed ANFIS scheme. The rotor flux level hardly changes in both the cases.

Table 1. Induction Motor Parameters

Parameter	Symbol	Value
Rated Power	P_{ratrd}	$50HP$
Rated Voltage	V	$480Volt$
Rated Frequency	F	$60Hz$
Pair of poles	P	2
Stator Resistance	R_s	0.087Ω
Rotor Resistance	R_r	0.228Ω
Stator Inductance	L_s	$0.8mH$
Rotor Inductance	L_r	$0.8mH$
Mutual Inductance	L_m	$34.7mH$
Moment of Inertia	J	$1.662Kg.m^2$

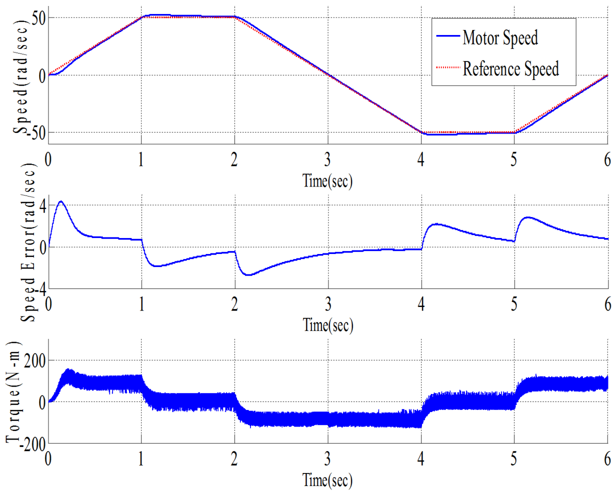

Fig. 7. Trapezoidal speed tracking with PI controller

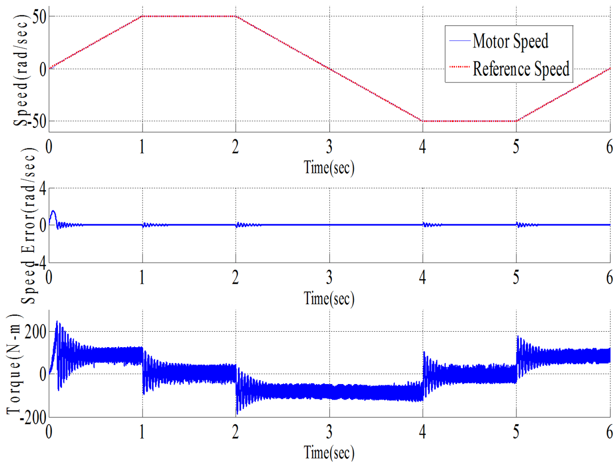

Fig. 8. Trapezoidal speed tracking with ANFIS controller

Figure (11 and 12) shows the speed transient and step torque change responses. The speed reference changes at time t=2.5 sec from 60 rad/sec to 120 rad/sec and load torque changes at time t=4 sec from 25 Nm to 150 Nm. The magnitude of rotor flux hardly changes at the speed and torque change in both the schemes. It is found that in the proposed scheme the speed changes without overshoot and it remains constant even when the torque changes.

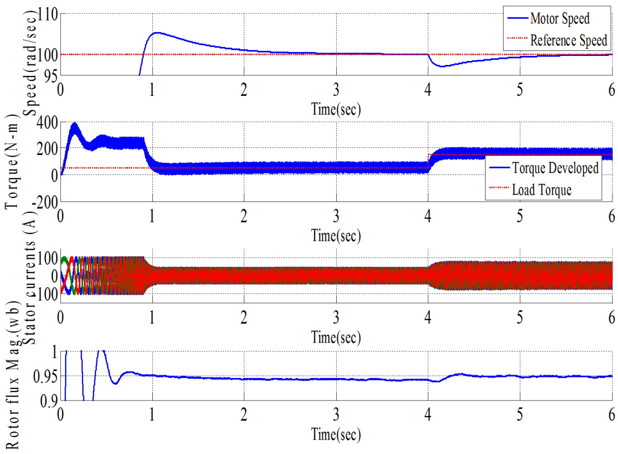

Fig. 9. Transient performance under step load with PI controller

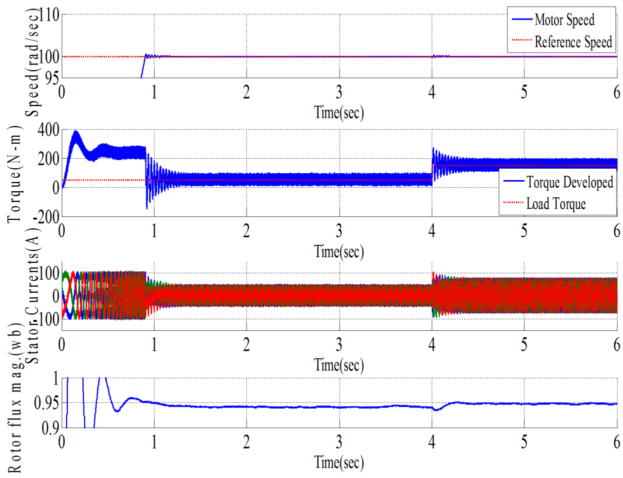

Fig. 10. Transient performance under step load with ANFIS controller

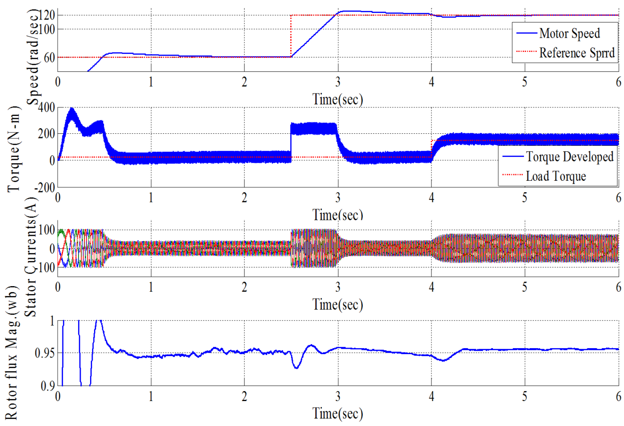

Fig. 11. Transient performance under step speed and step load with PI controller

6. CONCLUSION

This paper presents a comparative performance study of indirect vector control drive with PI controller and the proposed scheme consisting of neural estimator and ANFIS controller. Simulation results shows that the proposed scheme is more robust during the load changes and eliminates the transients during sudden

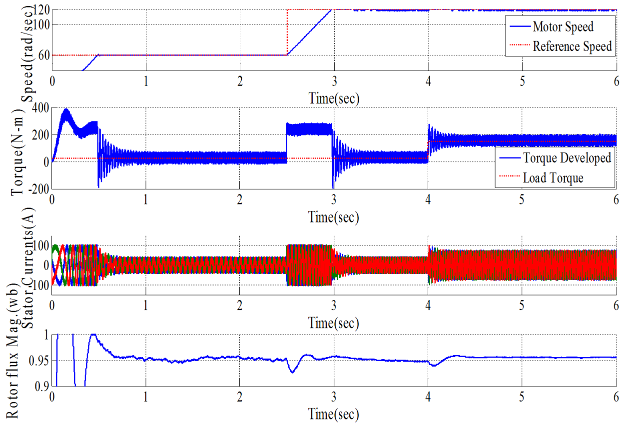

Fig. 12. Transient performance under step speed and step load with ANFIS controller

changes in speed. Overall simulation result shows that the proposed scheme with ANFIS controller has better performance over PI controller.

In ANFIS controller,only few rules have been utilized in the rule base to provide the control actions instead of full combination of of all possible rules.Therefore it is proposed for future work that the real coded Genetic Algorithm (GA) can be utilized to train the ANFIS controller instead of the hybrid learning methods that were used in ANFIS controller. Again GA can be used to find the optimal settings for the input and output scaling factors for this controller instead of the widely used trial and error method.

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