JPE 8-3-10

Steady State and Dynamic Response of a State Space Observer Based PMSM Drive with Different Controllers

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ABSTRACT

This paper deals with an investigation and evaluation of the performance of a state observer based Permanent Magnet Synchronous Motor (PMSM) drive controlled by PI (Proportional Integral), PID (Proportional Integral and Derivative), SMC (sliding mode control), ANN (Artificial neural network) and FLC (Fuzzy logic) speed controllers. A detailed study of the steady state and dynamic performance of estimated speed and angle is given to demonstrate the capability of the controllers.

Keywords: Artificial intelligence, Permanent magnet synchronous motor, Sliding mode control, State observer

1. Introduction

PMSMs (Permanent magnet synchronous motors) are extensively used in servo drives. These are also used in the field of electricity generation, solar water pumping, wind energy applications, etc. A PMSM has high air gap flux density, high power to weight ratio, large torque to inertia ratio, controlled torque at zero speed, high torque capability and high power factor. In addition, it operates smoothly even at very low speeds, is highly efficient, and is compact in size. [1]. It has to be operated in a closed loop control. A suitable method must be chosen so that these requirements can be met and desired performance is achieved. The idea behind using vector control in ac motor drives is to transform the ac machine, performance-wise, into an equivalent separately excited dc motor. This gives the performance of an ac machine similar to a separately excited dc machine while retaining the general advantages of an ac machine over a dc machine. The PI (Proportional Integral) and PID (Proportional Integral and Derivative) speed controllers are conventional speed controllers. They are easy to model and they can also easily be implemented in a closed loop control of the drive system [2-5]. The SMC (sliding mode controller) speed controller is another conventional speed controller which is easy to implement. It is capable of providing robust performance and this is considered a useful feature for the motor drive. To impart intelligence into the system, fuzzy logic controllers are used. In electric motor drives and motion control, the fuzzy logic controller is considered a promising alternative to conventional control techniques.
The fuzzy logic controller generates the reference

Manuscript received April 10, 2008; revised June 3, 2008
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current vector of the PMSM speed control based on the speed error and its change [6]. Fuzzy logic controllers are used for processes that have no simple mathematical model, for highly nonlinear systems, or where linguistically formulated knowledge needs to be processed.

The use of artificial neural networks (ANNs) is the most powerful approach in AI (artificial intelligence) [7-11]. One of the most outstanding features of ANNs is their capability to simulate the learning process. They are supplied with pairs of input and output signals from which general rules are automatically derived so that an ANN is capable of generating the correct output for a signal that has not been previously used. The torque control of a PMSM requires knowledge of the rotor position to perform an effective stator current control. Furthermore, an ac motor drive requires two current sensors and an absolute rotor position sensor for the implementation of the control strategy. Hence, control and operation without a rotor position sensor as shown in Fig.1 would enhance a PMSM's applicability to many cost sensitive applications and would also increase the mechanical robustness and reliability of the drive.

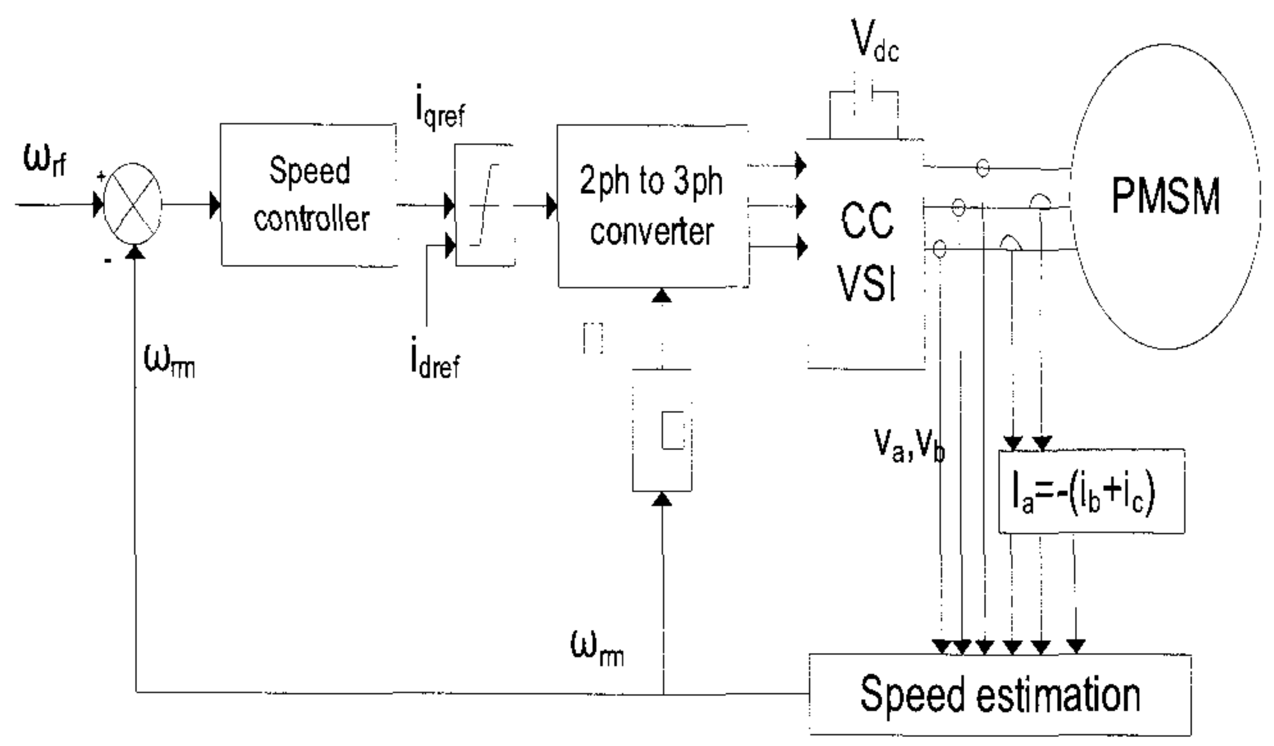

Fig. 1 Block diagram of sensorless control of PMSM

Sensorless control reduces maintenance requirements and ensures that the inertia of the system is not increased in sensor based drives during sensor failures. Among the few observer based position and speed estimation methods of a PMSM, the Extended Kalman Filter (EKF) method offers noise immunity and provides a powerful computation intensive back up control alternative [11-12]. In the present work an observer based on Extended Kalman Filter (EKF) for a PMSM is studied with various speed controllers such as PI, PID, SMC, fuzzy logic and ANN [5, 14]. The steady state and dynamic performance is compared in order to identify the best controller so that the observer based drive may be used where precise control is needed.

2. Modeling of PMSM

In a PMSM the permanent magnet can be considered as a fictitious equivalent constant current field excitation source. Thus, in the rotor reference frame, the rotor current space phasor is given as:

$$\bar{i} = cI_{rf} = ^{\text{constant}} \tag{1}$$

The flux linkage with the stator windings due to the permanent magnet in a surface mounted PMSM where the direct axis inductance is equal to the direct axis inductance ($L_d = L_q = L_m$) is given as:

$$\lambda_f = L_m I_{rf} \tag{2}$$

The equations of electromagnetic torque, direct axis current, quadrature axis currents and speed are given as [4]:

$$T_e = \frac{3}{2}\frac{P}{2}(\lambda_d i_q - \lambda_q i_d) \tag{3}$$

$$pi_d = -\frac{R}{L_d} i_d + \frac{L_q i_q}{L_d}\omega_{rm} Sin\,\theta_{rm} + \frac{1}{L_d}V_d \tag{4}$$

$$pi_q = -\omega_r \frac{L_d}{L_q} i_d + \frac{-R}{L_q} i_q + \frac{\lambda_f}{L_q}\omega_r Cos\theta_{rm} + \frac{1}{L_q}V_q \tag{5}$$

$$p\omega_r = (T_e - T_l - B\omega_r)/J \tag{6}$$

Substituting the value of T_e from (3) in (6):

$$p\omega_r = 3p(\lambda_d i_q - \lambda_q i_d)/(4J) - (B\omega_r + T_l)/J \tag{7}$$

The model of the motor is utilized to compute the stator currents.

3. Modeling of State Observer

A Kalman filter provides a solution that directly takes care of the effects of the disturbance noises including system and measurement noises. This assumes that measurement noise and disturbance noise are uncorrelated.

The Kalman filter approach is a viable and computationally efficient candidate for online estimation of the speed and rotor position. This is possible because a mathematical model describing PMSM dynamics is sufficiently well known.

Fig.2 shows the observer based speed estimation block. The motor model equations contain the states i_d, i_q, ω_{rm} and θ_{rm}, where the latter two variables are estimated. The torque control of a PMSM requires knowledge of the rotor position to perform an effective stator current control. The rotor position can be determined based on sensed voltages and currents, considering that the motor is running at a speed ω_r whereas the model starts with an assumed rotor speed ω_{rm}.

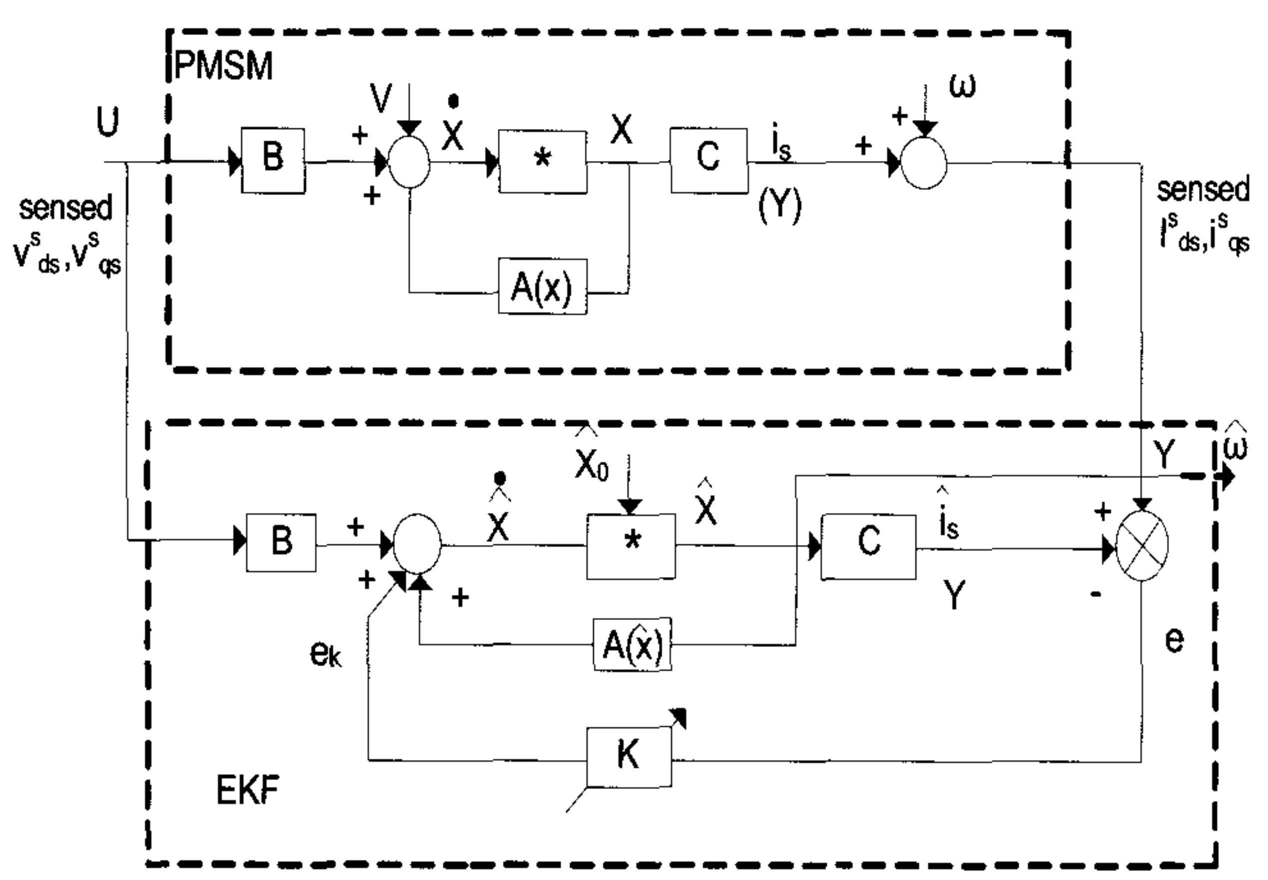

Fig. 2 Structure of EKF

The assumed rotor position θ_{rm} lags behind the rotor position θ_r by $\delta\theta$ radians. As shown in Fig.3. The relations between actual and assumed rotor positions and rotor speeds are as follows [4]:

$$\theta_r = \int \omega_r dt \tag{8}$$

$$\theta_{rm} = \int \omega_{rm} dt \tag{9}$$

$$\delta\theta = \theta_r - \theta_{rm} = \int (\omega_r - \omega_{rm}) dt \tag{10}$$

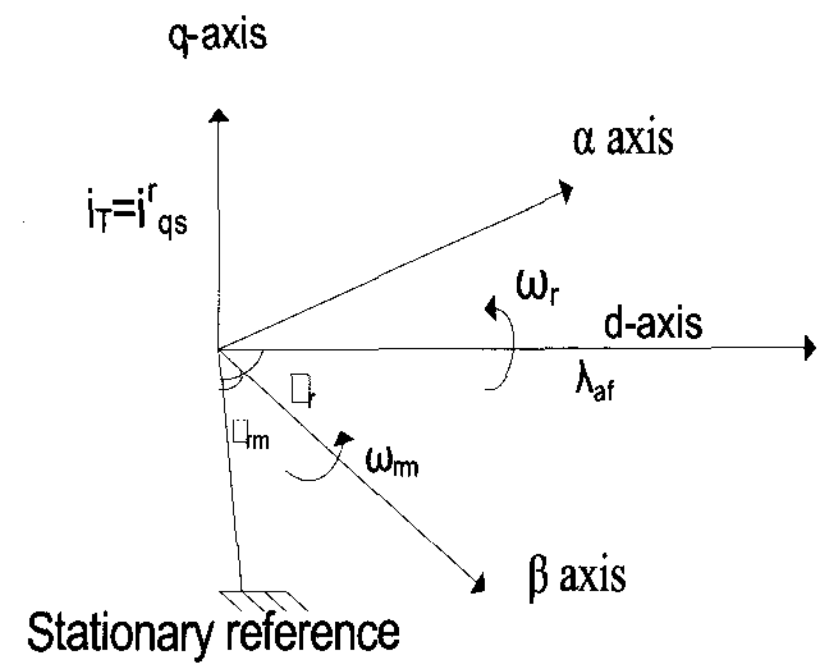

Fig. 3 Phasor diagram corresponding to an error between the actual and assumed rotor position

The dynamic model of the motor in state variable form can be expressed as:

$$\frac{dX}{dt} = A(X) + BU \tag{11}$$

$$Y = CX \tag{12}$$

where $X = [i_d \quad i_q \quad \omega_{rm} \quad \theta_{rm}]$ is the state vector, $U = [v_d \quad v_q]^T$ is the input vector, Y= $[i_d \quad i_q]^T$ is the output vector, and the matrices $A(X)$ and B are parameter matrices and C is a constant matrix. The stator phase voltages in a dq rotor frame can be expressed in terms of their abc-reference frame values. The sensed motor phase currents i_a, i_b, and i_c are transformed to the rotor reference d-q frame in a way similar to the voltages. The state equations of the motor are given in (11) and (12). These state equations can be used for the design of a state observer. Now, if one only wants to estimate some of the state variables say $[i_d \quad i_q]^T$ then the standard form of the state observer equation is given by:

$$\frac{d(X)}{dt} = A(X,V) + G(\hat{I} - I) \tag{13}$$

V is the sensed input vector and is equal to $[v_d \quad v_q]$. It is obtained by transforming the phase voltage (v_a, v_b, v_c)

into the rotor reference frame using the estimated rotor position, not the actual rotor position. The phase voltages are sensed from the terminals of the motor. The current state vector $I = [i_d \quad i_q]$, obtained by transforming the sensed value of phase currents (i_a, i_b, i_c) into the rotor reference frame using the estimated rotor position, $\hat{I} = [\hat{i}_d \quad \hat{i}_q]$ is the estimated value obtained by the solution of (13). In (13), G is the observer gain matrix, which is the result of tuning the system in such a way, that (13) becomes stable.

G matrix can be given as:

$$G = \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \\ g_{31} & g_{32} \end{pmatrix} \tag{14}$$

Using this matrix, the equations (4), (5) and (7) can be expressed in detail as:

$$pi_d = -\frac{R}{L_d} i_d + \frac{\omega_r L_q}{L_d} i_q + \frac{1}{L_d} v_d + g_{11}(\hat{i}_d - i_d) + g_{12}(\hat{i}_q - i_q) \tag{15}$$

$$pi_q = -\frac{\omega_r L_d}{L_q} i_d + \frac{(-R)}{L_q} i_q + \frac{-\lambda_f}{L_q}\omega_r + \frac{1}{L_q} v_q + g_{21}(\hat{i}_d - i_d) + g_{22}(\hat{i}_q - i_q) \tag{16}$$

$$p\omega_r = 3P(\lambda_d i_q - \lambda_q i_d)/(4J) - (B\omega_r + T_l)/J + g_{31}(\hat{i}_d - i_d) + g_{32}(\hat{i}_q - i_q) \tag{17}$$

In such a motor the electrical time constant is much smaller than the mechanical time constant, that is, electrical sub dynamics are much faster than mechanical dynamics. Therefore, the error in electrical quantities can be used as feedback to rectify the estimated values of both electrical and mechanical quantities. This is the basic concept used in the observer model defined by (15), (16) and (17) [12-13].

4. Field Weakening

In small rating drives there is no need for flux weakening. However, it is not possible to achieve direct field weakening for large rating drives owing to the permanent magnet construction. For these drives, the effect of field weakening can be obtained by controlling the stator currents in such a way that the stator current space phasor in the rotor reference frame should contain a direct axis component i_{sd} along the negative direct axis of the rotor reference frame. In addition to the quadrature axis stator current component i_{sq}, the demagnetizing current $-i_{ds}$ is injected on the stator side. As shown in Fig.4 in flux weakening mode, i_q is controlled so that its maximum value is limited by

$$i_q^* = \sqrt{I_s^2 - |i_{ds}|^2} \tag{18}$$

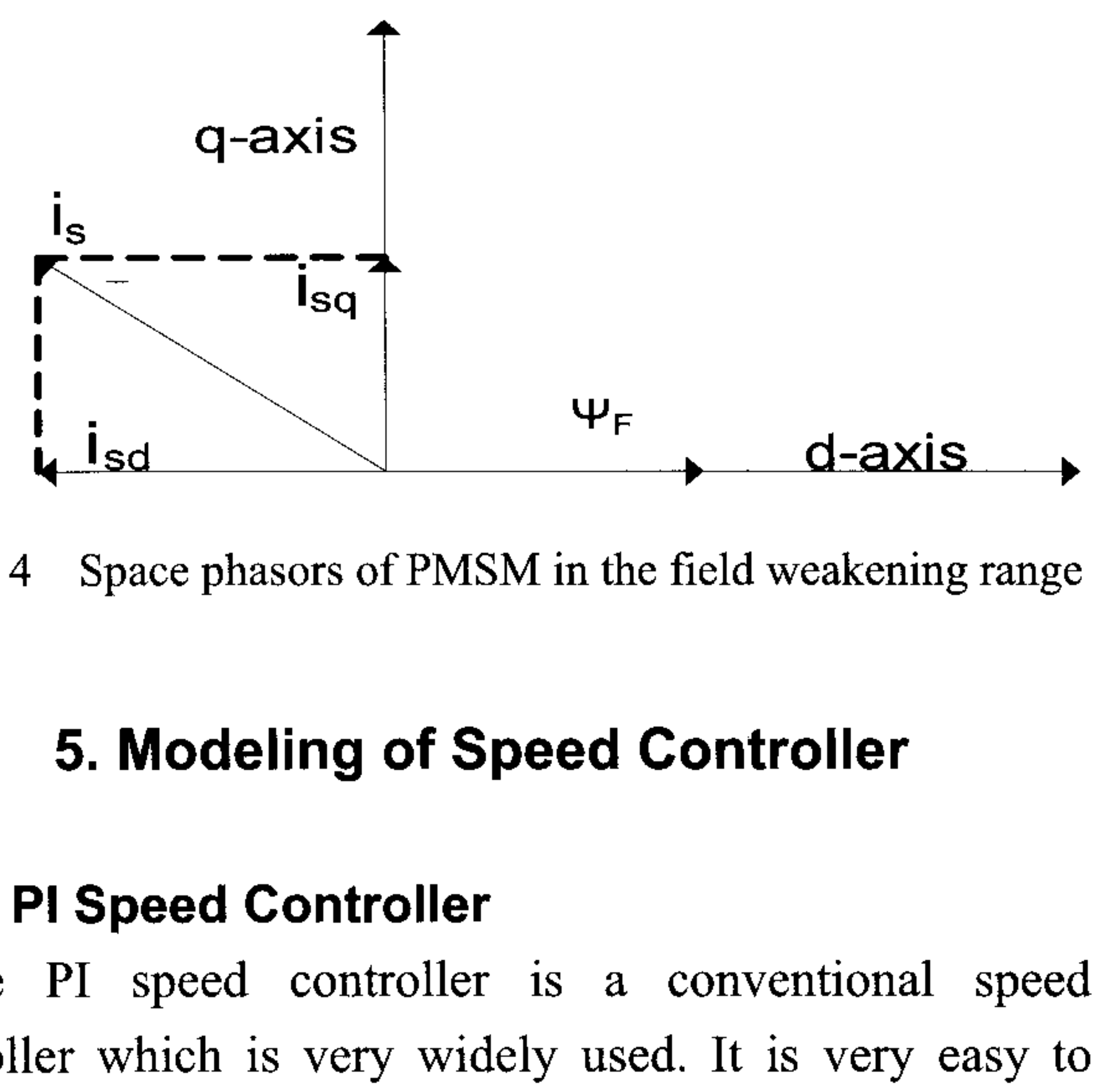

Fig. 4 Space phasors of PMSM in the field weakening range

5. Modeling of Speed Controller

5.1 PI Speed Controller

The PI speed controller is a conventional speed controller which is very widely used. It is very easy to model and it can also be easily implemented in the closed loop operation of the drive system. It consists of two control parameters, namely, the proportional and the integral gains. By properly tuning these parameters the desired level of performance can be achieved. The block diagram of the PI speed controller is developed in SIMULINK. In the PI speed controller, the motor speed is compared with the reference speed and the speed error is obtained at the nth sampling interval as [15]:

$$\omega_{e(n)} = \omega^*_{r(n)} - \omega_{r(n)} \tag{19}$$

The output of the speed controller gives the reference torque. Hence the output of the speed controller at the nth sampling interval is [4, 5]:

$$T_{(n)}^* = T_{(n-1)}^* + K_p(\omega_{e(n)} - \omega_{e(n-1)}) + K_I \omega_{e(n)} \tag{20}$$

For constant air gap flux operation, the reference quadrature axis current is given as:

$$i^*_q = T_{(n)} / K_t \tag{21}$$

where, $\omega_e(n)$ is the speed error at nth instant, $\omega^*_{r(n)}$ is the reference speed at the nth instant, $\omega_{r(n)}$ is the motor speed at the nth instant, $\omega_{e(n-1)}$ is the speed error at the $(n-1)^{th}$ instant, $T_{(n)}$ and $T_{(n-1)}$ are the reference torque at the nth and (n-1)th instants, K_p and K_I are the proportional and integral gains of the speed controller, i^*_q is the reference quadrature axis current, and K_t is the torque constant. The limiter is used to limit the maximum value of the output of the speed controller. The motor current and device current of the converter dictate the limit of the current.

5.2 PID Speed Controller

The output of the conventional PID speed controller is the reference torque at the nth sampling interval and is given as:

$$T_{(n)}^* = T_{(n-1)}^* + K_p\{\omega_{e(n)} - \omega_{e(n-1)}\} + K_I \omega_{e(n)} + K_D\{\omega_{e(n)} - 2\omega_{e(n-1)} + \omega_{e(n-2)}\} \tag{22}$$

where K_P, K_I and K_D are the controller gains of the PID speed controller and n is the sampling index.

5.3 Fuzzy Logic Controller

In a fuzzy logic controller (FLC), the system control parameters are adjusted by a fuzzy rule based system, which is a logical model of the human behavior for process control. A typical topology with $e_{(k)}$ as the error and c_e as the change in error in the speed command of the fuzzy speed controller is shown in Fig.5 as:

$$\text{where, } e_{(k)} = \omega^*_{(k)} - \omega_{(k)} \tag{23}$$

$$\text{and } C_e = e_{(k)} - e_{(k-1)} \tag{24}$$

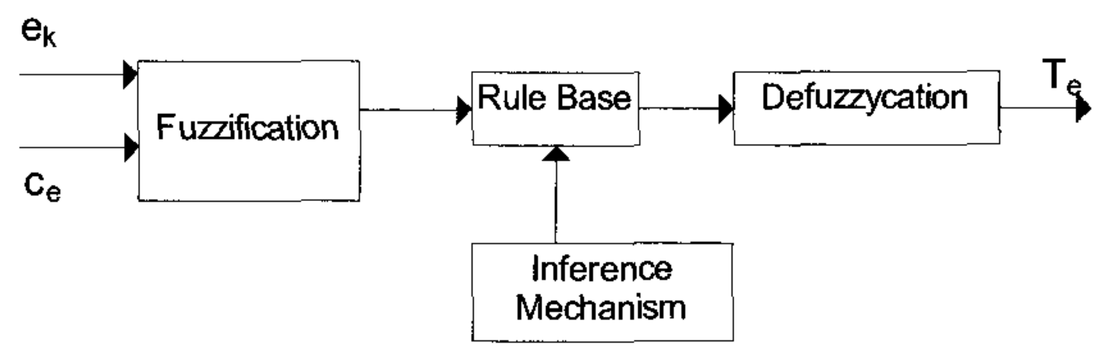

Fig. 5 Fuzzy Logic speed controller

The FLC is constituted of three stages: fuzzification, rule base and defuzzification. An FLC does not require the exact mathematical model; instead its structure is knowledge based or rule based. These rules are imprecise and are expressed in terms of linguistic variables, etc. [3, 7].

5.4 Sliding Mode Controller

The SMC is shown in Fig.6 [2, 3, 15]. To overcome the problems of overshoot and oscillations associated with the use of a PID speed controller, the SMC controller becomes important. The sliding mode control makes system motion robust with respect to system parameter variations, unmodeled dynamics and external disturbances. In addition, this technique provides efficient control laws for linear and nonlinear plants. Another distinguishing feature is its order reduction capability, which enables simplification of design and system decoupling. With these advantages, the sliding mode control is a promising area for motor drive system. In this case, the speed locus is a straight line lying in the second and fourth quadrants of the phase plane of the speed error and acceleration of the drive system. Switching along the locus is achieved depending on the values of speed error and acceleration, and, therefore, it can be called the speed locus. The output of the sliding mode controller is limited through a limiter and the signal obtained is used to determine the reference torque T_e^*.The block diagram in Fig. 6 represents the switching of the structure of the system. Here S_1 and S_2 are the switching functions whose values are decided as:

$$S1 = +1, \text{ if } Zx_1>0 \quad -1, \text{ if } Zx_1<0 \tag{25}$$

$$S2 = +1, \text{ if } Zx_2>0 \quad -1, \text{ if } Zx_2<0 \tag{26}$$

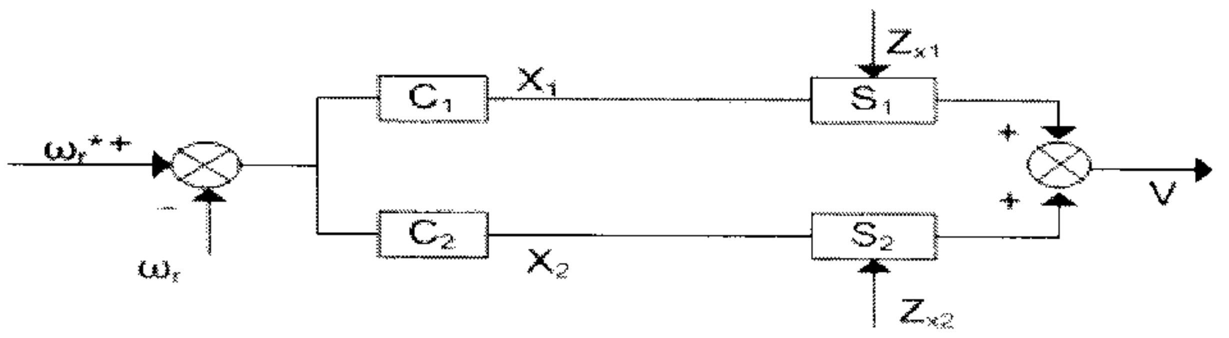

Fig. 6 SMC speed controller

where x_1 is the speed error and x_2 is the derivative of the speed error.

The output of the SMC is given by $V= C_1x_1S_1 + C_2x_2S_2$, where C_1 and C_2 are controller gains on the speed locus.

The switching hyper plane function is expressed as $Z = K_1x_1 + K_2x_2$, Here, K_1 and K_2 are adjustable parameters. The limiter limits the output of the SMC and the output of the limiter is considered the reference torque.

5.5 Neural Network Controller

The main objective of the ANN speed controller is to provide an accurate and fast response making the whole system immune to the effect of load variations, parameters changes, noise, temperature, etc [8-11]. Fig. 7 shows a multilayer neural network controller, which has been trained to replace the conventional controller. In this multilayer feed-forward artificial neural network there is an input layer, an output layer, and between the input and output layers there are so called hidden

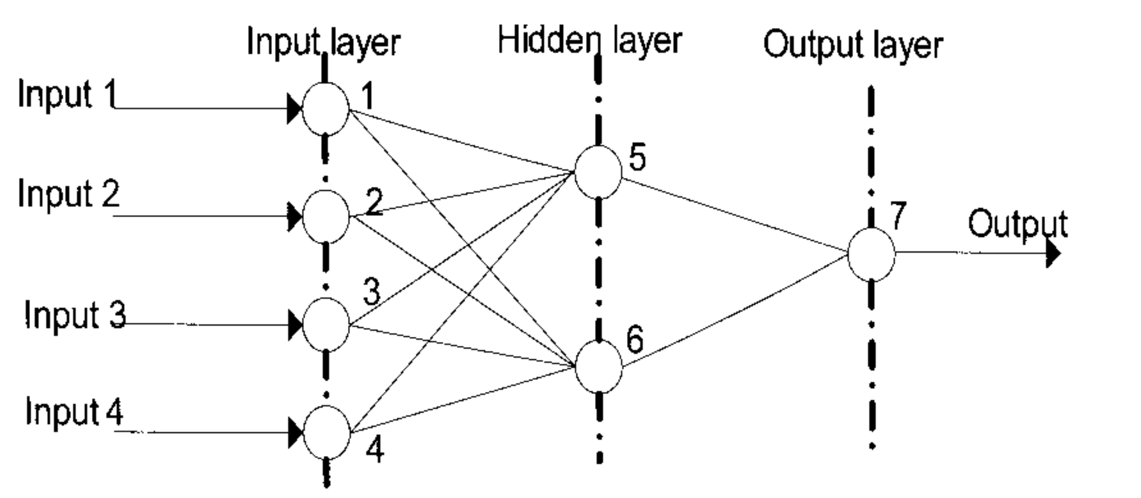

Fig. 7 Multilayer feed-forward artificial neural network with one hidden layer

layers. The input and output of the ANN controller are determined from the knowledge of the conventional PI controller. Here, in the input of the controller, the error in the speed is given as the difference between the reference speed and the sensed speed of the motor that is obtained through the speed estimation block of Fig.1. The PI controller for the plant as a vector controlled PMSM drive has been replaced by a neural network controller which is static, thus simplifying the control implementation. The tuning effort of an AI based system can be less than that of a conventional system. Such a system leads to reduced development time.

The output of the ANN controller is i_q^* the quardrature axis reference current for the PMSM. Therefore, the number of the neuron in the output layer is one. In multilayer networks the tan-sigmoid transfer function 'tansig' is used in the back propagation algorithm. One iteration of the back propagation algorithm can be written as $X_{k+1} = X_k - \alpha_k g_k$ where X_k is a vector of current weights and biases, g_k is the current gradient, and α_k is the learning rate. The following code creates a training set of inputs p and targets t. For batch training, all of the input vectors are placed in one matrix. p = [-1 -1 2 2; 0 5 0 5]; t = [-1 -1 1 1];

Here the function minmax is used to determine the range of the inputs to be used in creating a feedforward network as:

net=newff(minmax(p),[3,1],{'tansig','purelin'},'traingd'));

The training parameter to train the neural controller as shown in Fig. 8 with the goal of minimizing the error up to 1e-5 is as follows:

net.trainParam.goal = 1e-5;

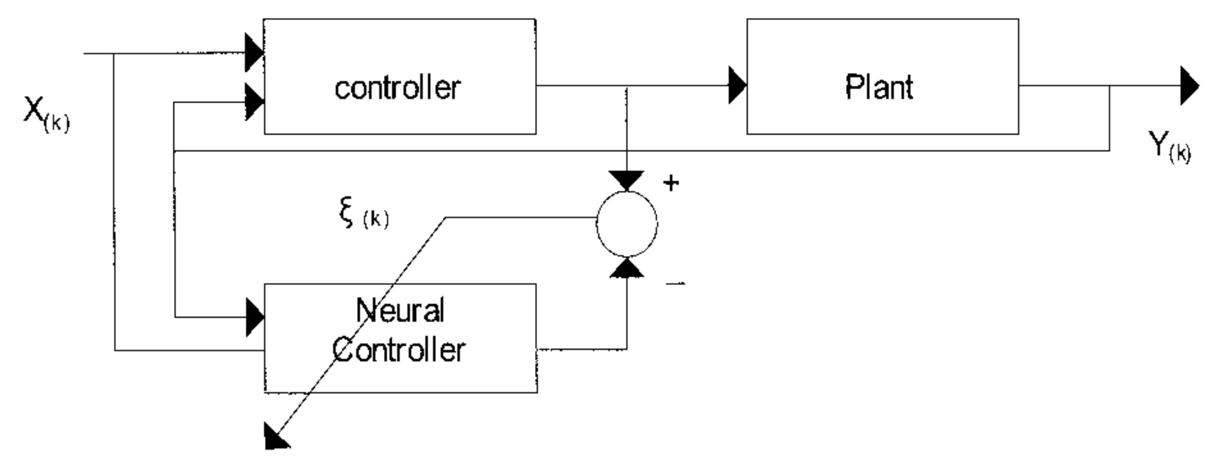

Fig. 8 Training of neural controller to emulate actual controller

A mechanism of online weight changing has been provided so that the motor controller becomes an adaptive one. The ANN controller is provided with an initial set of inputs and biases which also ensures the stability of the system. Furthermore, this set of weights and biases is changed in real time at every sampling instant using the back propagation algorithm. These two requirements are critical for the online design of a successful adaptive speed controller.

6. MATLAB Model

An observer block for sensorless control of a PMSM motor is developed in MATLAB. Three phase voltages and currents are taken as input to the observer. Using (13) to (17) the observer block is simulated. The flux weakening block is also added in the model to run the PMSM motor above the base speed. In order to get desired output voltage and current the pulses are generated using PWM techniques at 16 kHz[16] and are applied at the gate terminals of the IGBT (Insulated Gate Bipolar junction Transistor) based inverter as shown in the MATLAB model of the observer based PMSM of Fig.9.

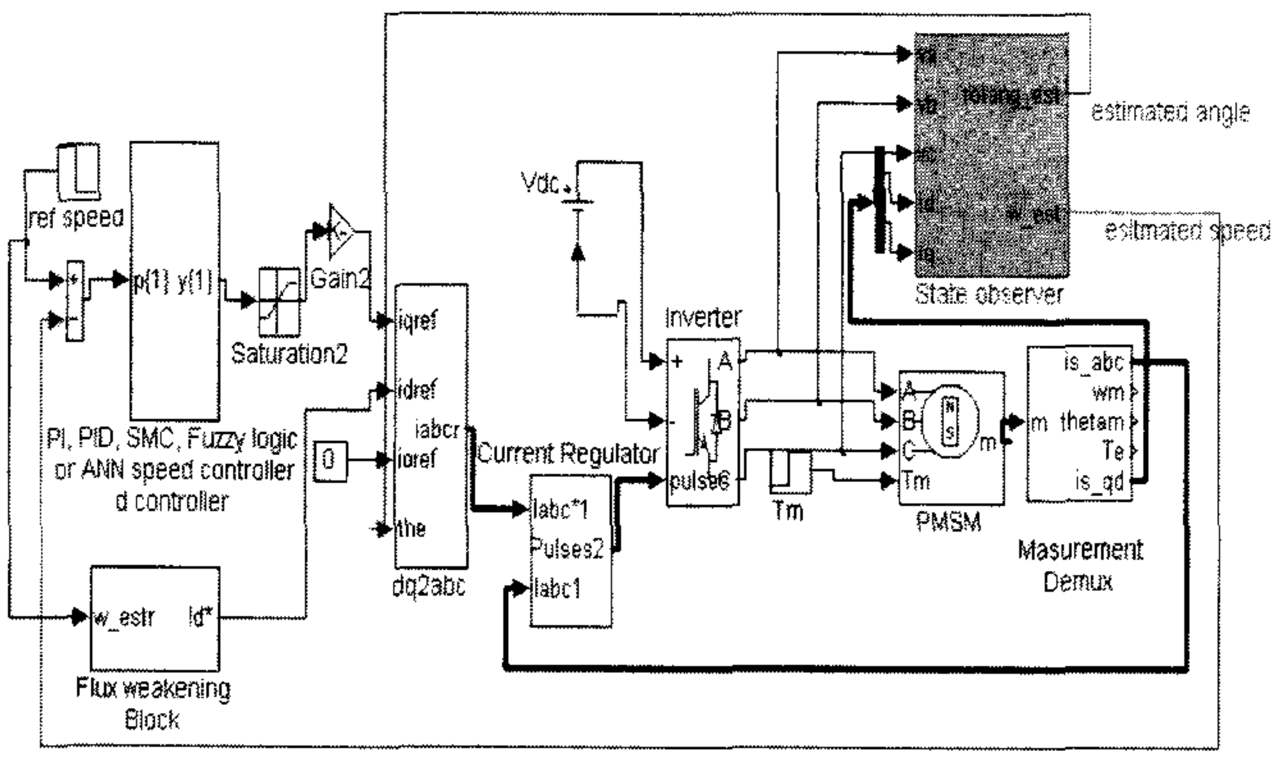

Fig. 9 MATLAB model of the observer based PMSMdrive

Estimated angle and estimated speed are calculated using the gain matrix of (14) and are the output of the observer block which in turn are fed back to the speed controller of the model in order to minimize the speed error and run the motor at the desired reference speed. The value of i_d is zero on or below the base speed. The flux weakening block is developed to get different values of i_d in order to achieve a speed higher than the rated speed. There are speed estimation and position estimation blocks inside the observer block of the model.

7. Results and Discussion

The motor is started at a reference speed of 700 rpm with 1Nm mechanical load and the performance is studied during starting, steady state and transient conditions. The speed response, torque response, current response and angle response for sensed and estimated conditions are studied in Fig.10, Fig.11, Fig.12 and Fig.13 for PI, PID, SMC, fuzzy logic and artificial neural network (ANN) speed controllers on the state space observer based speed and angle estimation of a PMSM. The observer with SMC, PI and PID controller attains 700rpm in 0.030 sec, with neural network controller it attains the same in 0.023sec, and with the fuzzy logic controller it attains the speed in 0.028sec. The PID and PI speed controllers take 0.03sec and 0.034sec, respectively.

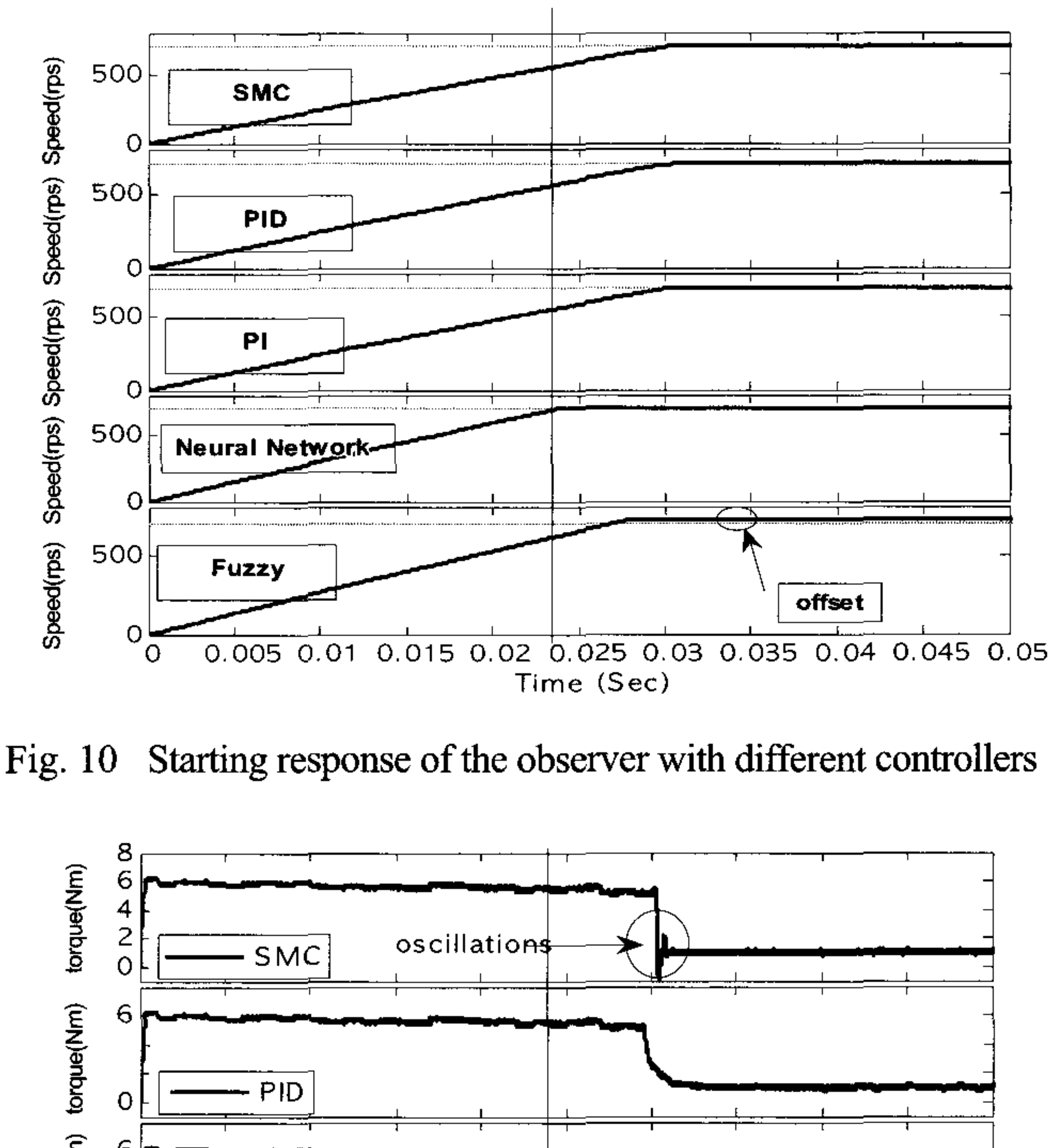

Fig. 10 Starting response of the observer with different controllers

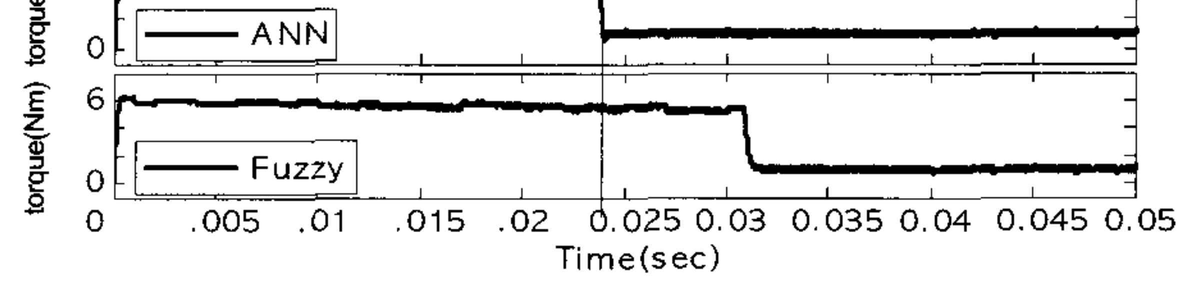

Fig. 11 Torque response during starting with different controllers

Fig.11 shows the torque response of the state observer with different controllers. With sliding mode controller the torque settles down after transients with oscillations of more than 4 Nm whereas with neural network controller the torque settles down smoothly and faster response is seen compared to fuzzy logic, PI and PID speed controllers. Fig.12 shows the current response with different controllers and the ripples are seen in the SMC controller under transient conditions. Fuzzy, PID, PI and neural network speed controllers give an improved and smooth response but the response of the neural network controller is faster than the fuzzy, PID, and PI controllers and is smooth under transient conditions. Fig. 13 shows the estimated and actual angle during the starting of the motor.

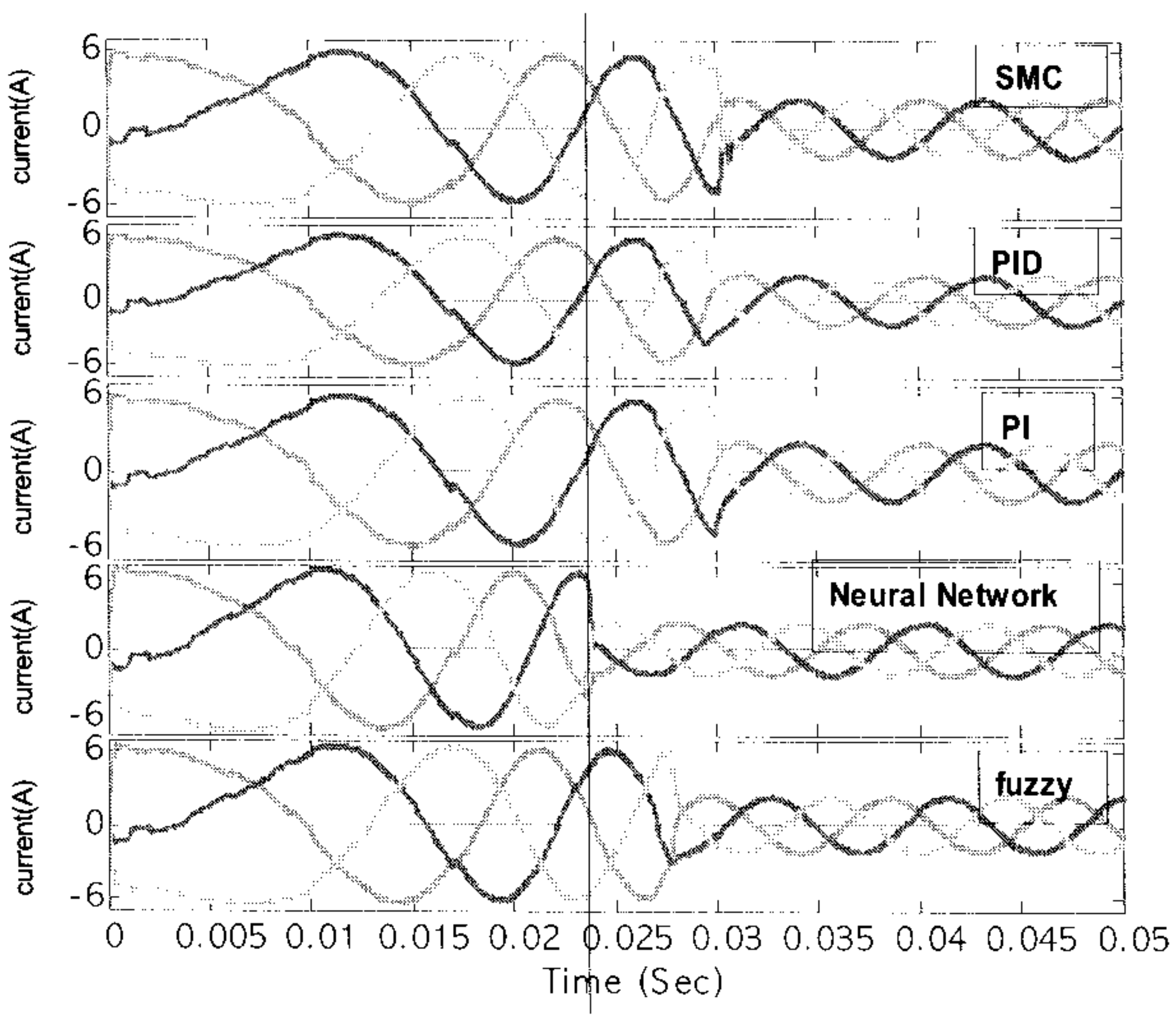

Fig. 12 Current response during starting with different controllers

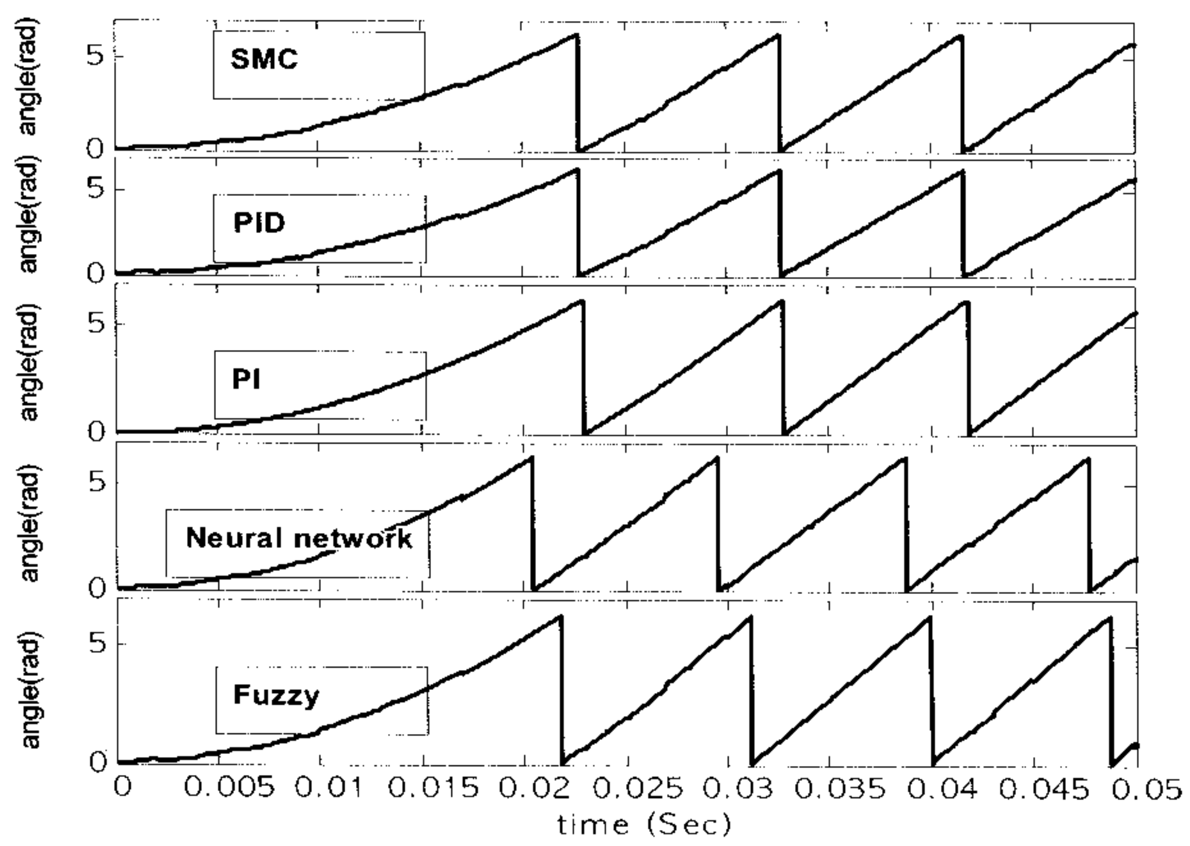

Fig. 13 Estimated angle during starting with different controllers

Steady state performance is given in Fig.14. There is steady state error of more than 15 rpm in the fuzzy logic controller. With the SMC the error is 0.05 rpm, but the motor experiences oscillations before settling to its reference speed. With the neural network controller there is a steady state error of 3rpm, but the controller speed of 700rpm is achieved smoothly.

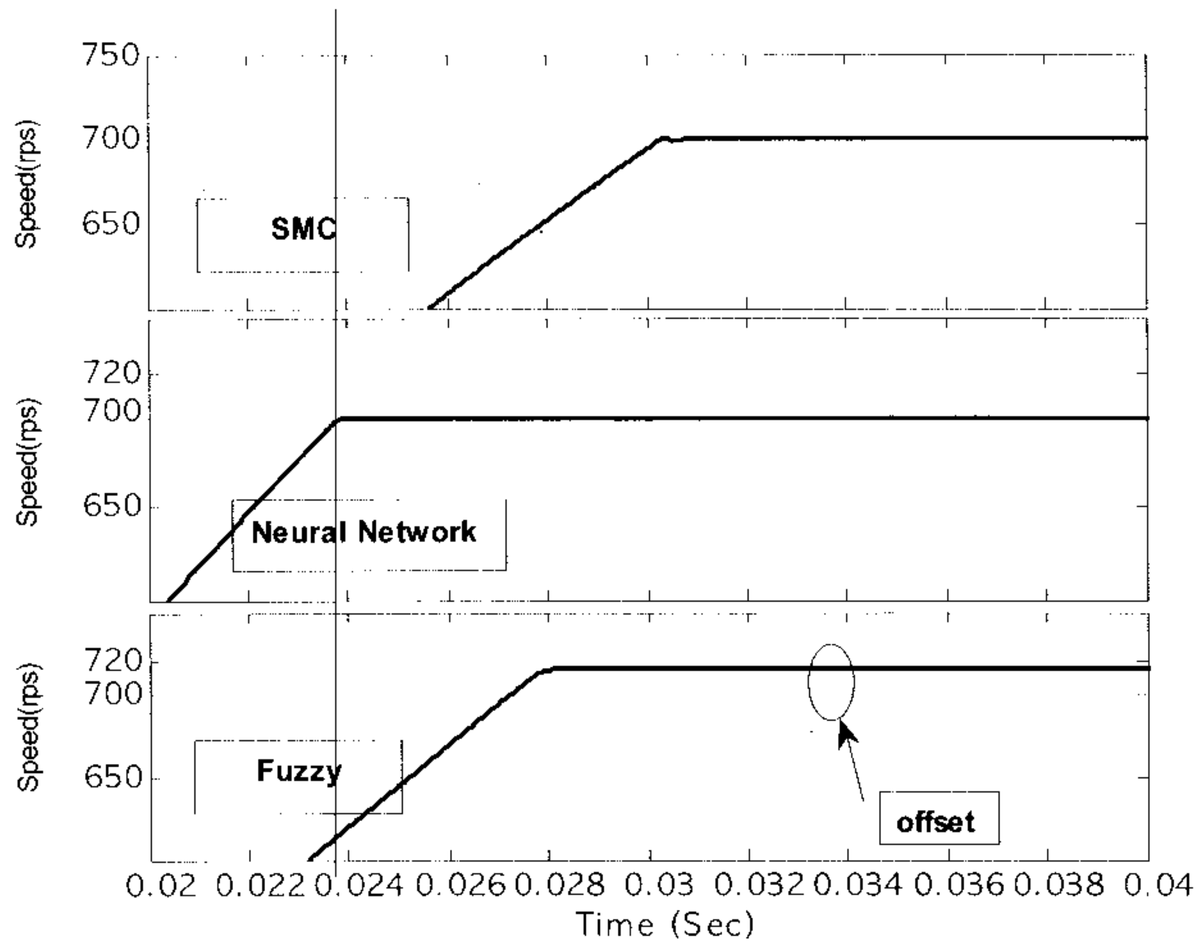

Fig. 14 Closed view of speed response during starting with SMC, NN and fuzzy controllers

The PMSM drive is started and operated in flux weakening mode with the state observer. The step from 700 rpm to a speed of 1400 rpm, higher than its rated speed of 1200 rpm, is given as reference and is achieved with all the controllers. Fig.15 shows the speed response of all the controllers in flux weakening mode.

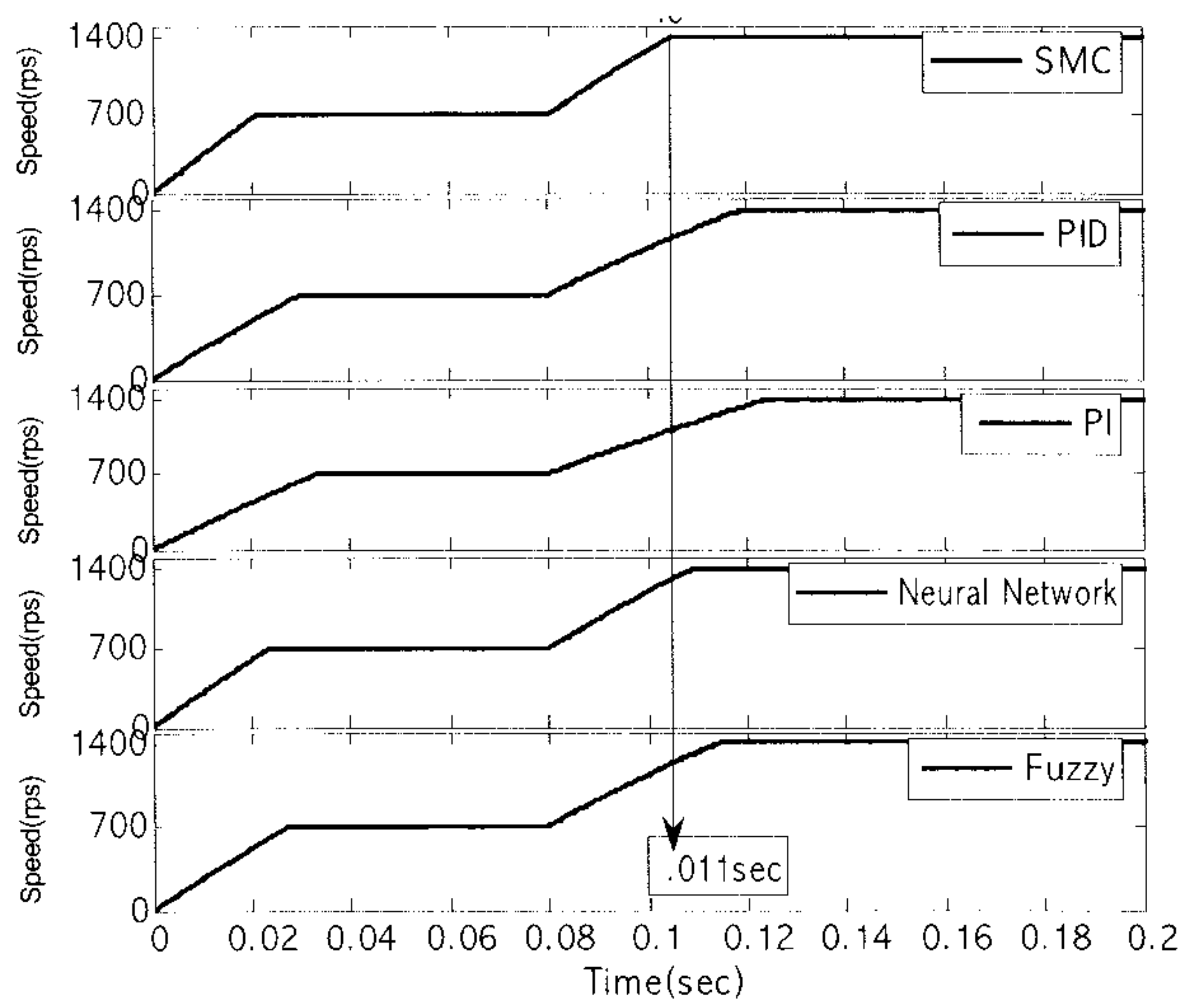

Fig. 15 Speed in flux weakening and load perturbation

The neural network controller gives improved performance as it starts and settles faster without oscillations and also takes less time in achieving the target. The performance is studied for load perturbation. The load is increased from 1Nm to 3Nm in flux weakening mode. Fig.15 shows that speed remains unchanged during load perturbation with all the controllers. Fig.16 and Fig.17 show the torque and current response of all the speed controllers in flux weakening mode.

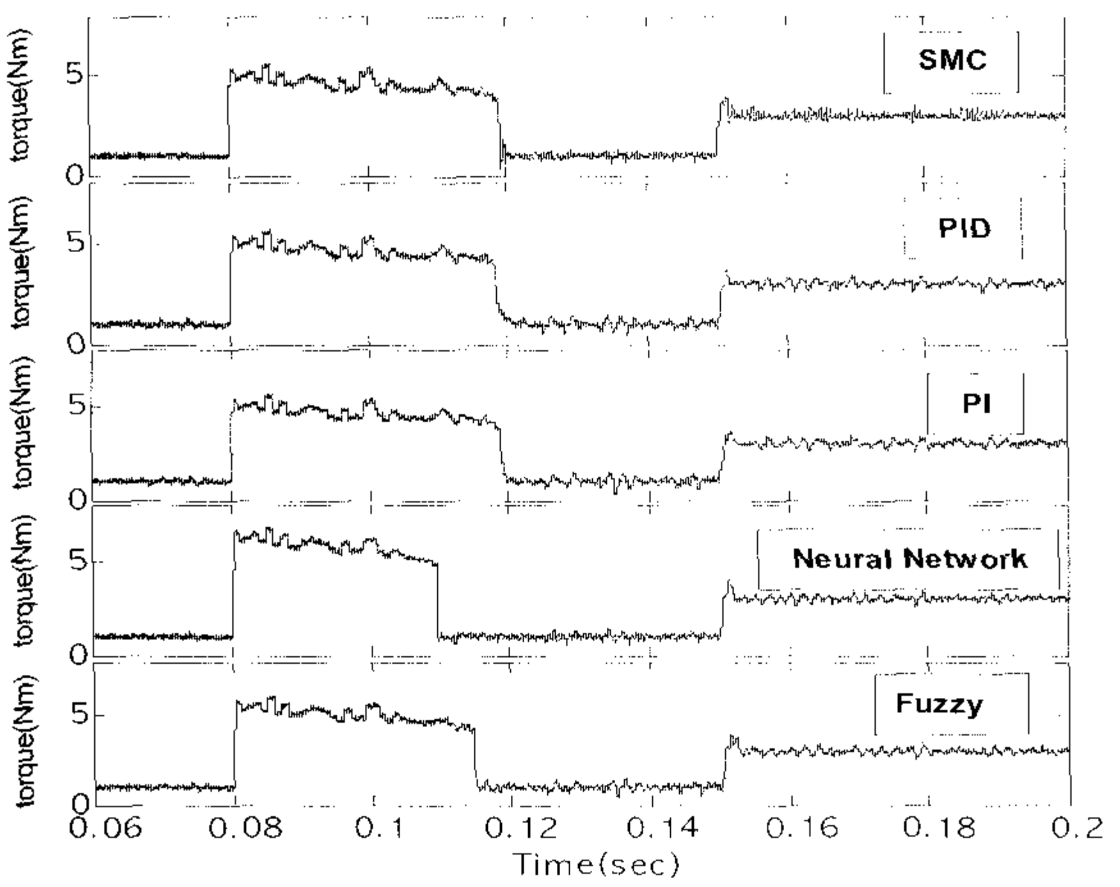

Fig. 16 Torque in flux weakening and load perturbation

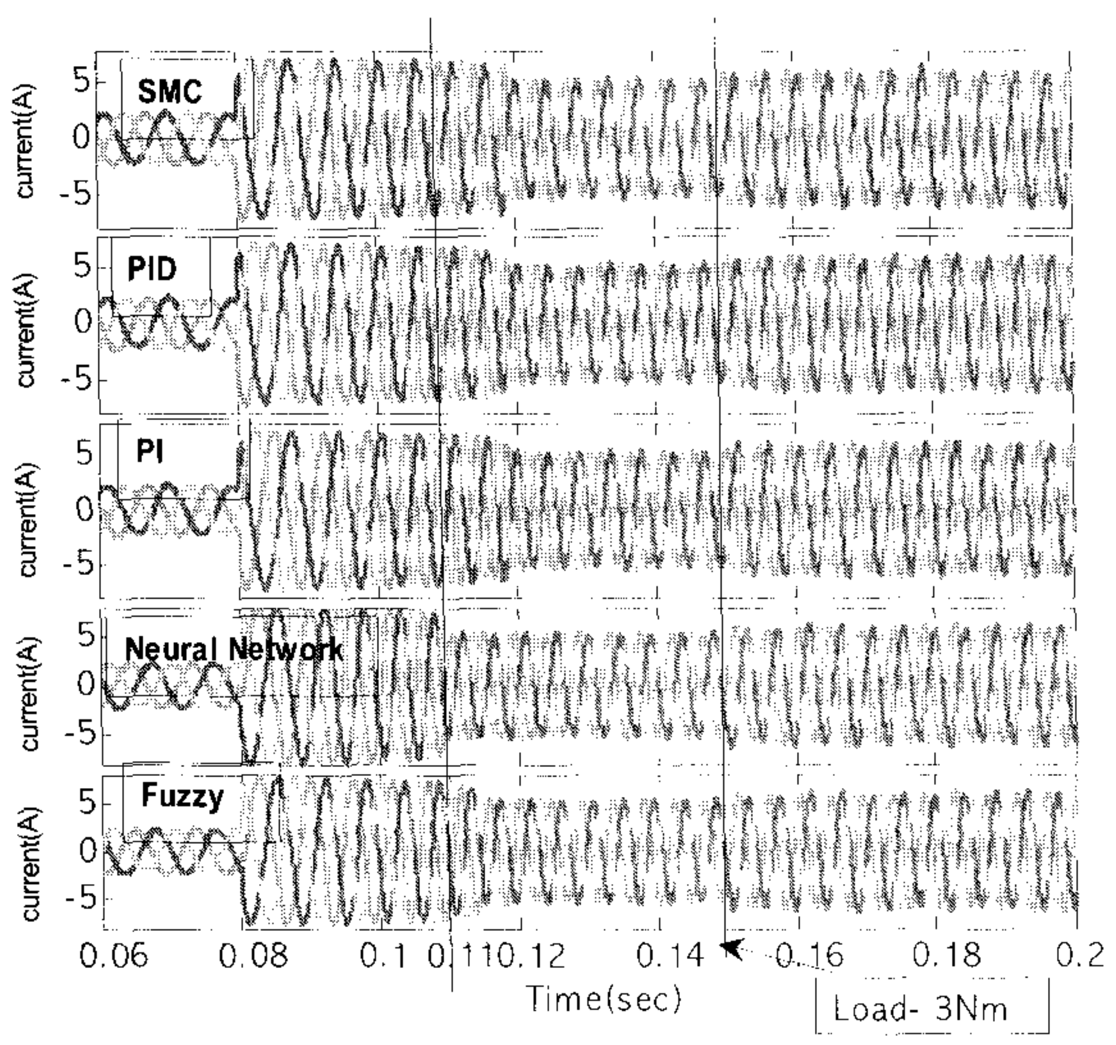

Fig. 17 Current during flux weakening and load perturbation

Fig.16 and Fig.17 show the satisfactory performance in torque and current curves, respectively, with load perturbation at 0.15 sec in flux weakening mode. The observer based system is also studied for speed reversal from 700 rps to -700 rps and the load is increased from 1 Nm to 3 Nm at 0.15 sec. Fig. 18, Fig. 19 and Fig.20 show the response of the system at speed reversal, current and torque response, respectively, during speed reversal.

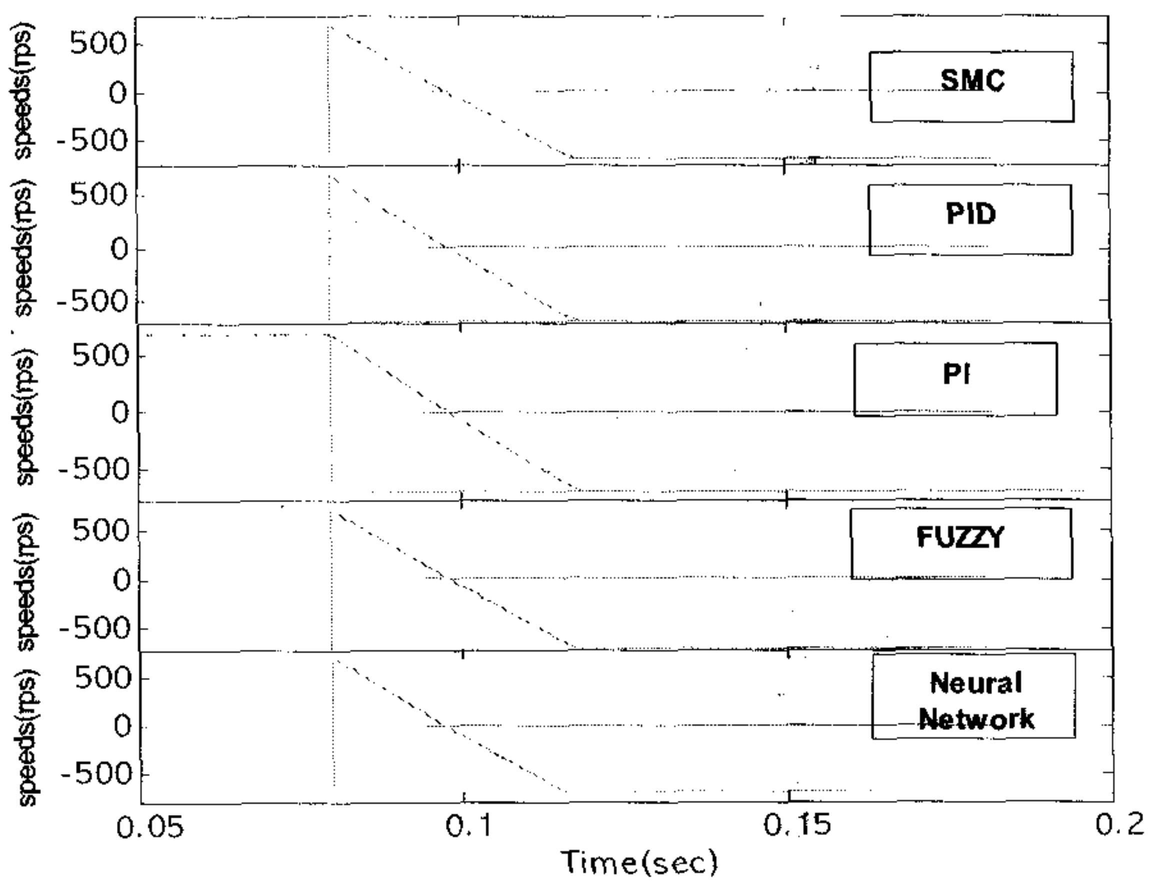

Fig. 18 Speed reversal and load perturbation

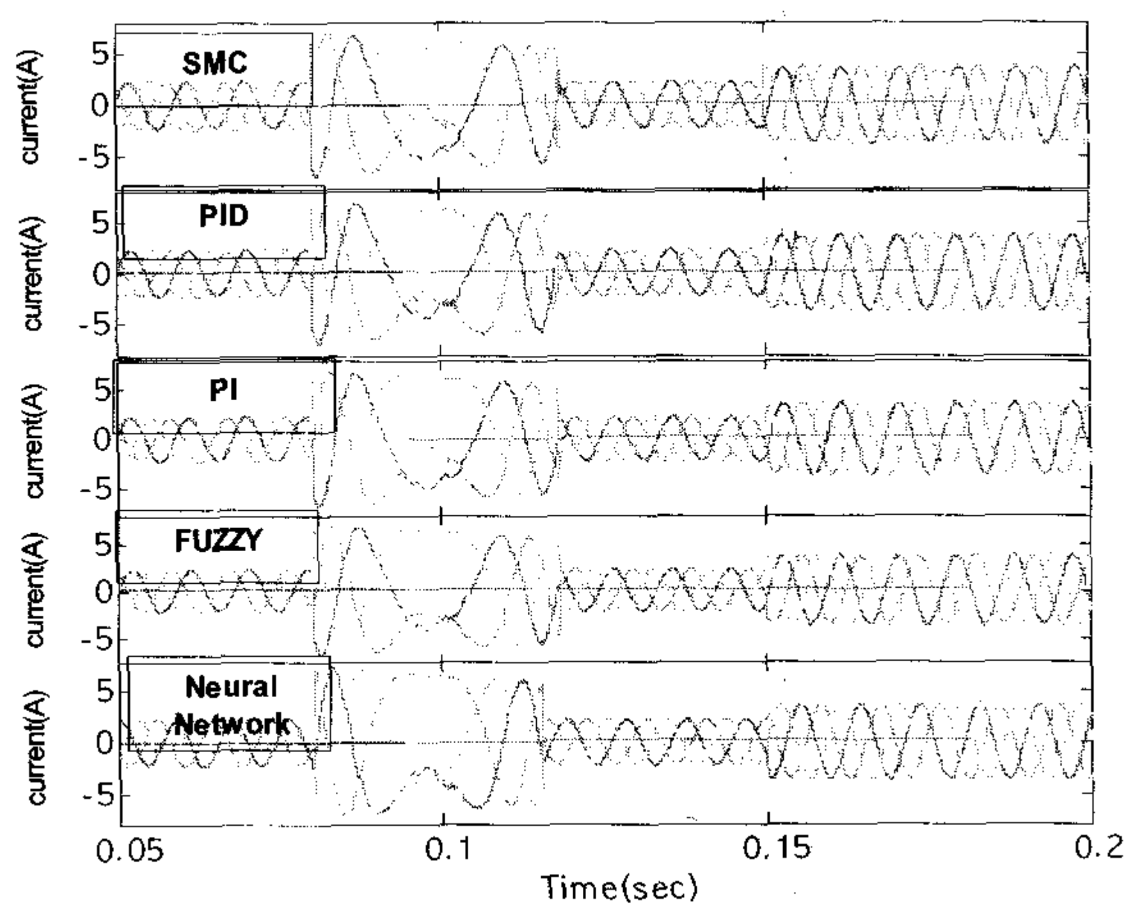

Fig. 19 Current during speed reversal and load perturbation

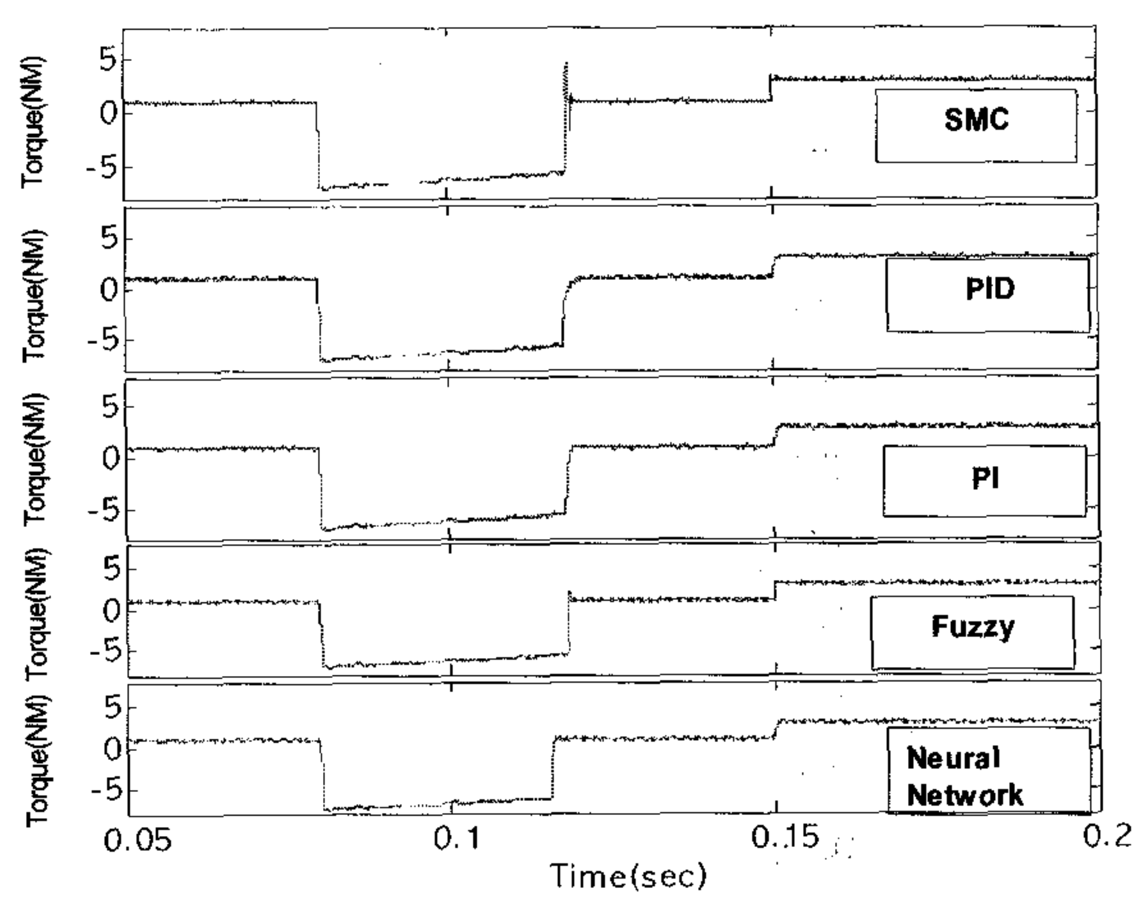

Fig. 20 Torque during speed reversal and load perturbation

The results indicated in Fig.17, Fig.18 and Fig.19 show that the observer based system responds faster with the neural network controller during speed reversal, while at load perturbation there is no change in speed.

8. Conclusion

The obtained results have clearly demonstrated that for a state space observer based PMSM drive, the neural network controller is the fastest among SMC, PI, PID, fuzzy and neural network speed controllers. The speed, torque and current response verify that with neural network control the state space observer based PMSM drive is robust and smooth control is obtained for various disturbances such as starting, steady state, field weakening speed reversal and load perturbation. Hence, it may be used where precise control is needed such as in satellites and aircraft operation, etc.

Table 1 Parameters of PMSM

Power Rating of the motor	1.1 kW
Number of pole pairs p	4
Armature resistance R_s	2.875Ω
Magnet flux linkage λ_f	0.175Wb
d-axis inductance L_d	8.5mH
q-axis inductance L_q	8.5mH
Phase voltage V	220V
Moment of inertia J	0.0008kg.m^2

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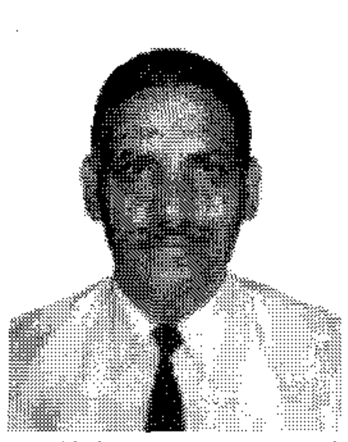

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