High Dynamic Performance of PMSM Drive Using MIMO Fuzzy Controller

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Abstract: This paper presents modeling and analysis of electric drives with Permanent Magnet Synchronous Motors (PMSM). This method has high-performance, robust, speed controller of PMSM drive with neural network tuned fuzzy Controller for controlling multi inputs multi outputs (MIMO) systems. The structure of MIMO fuzzy controller is divided into single input single output. A MIMO fuzzy is designed and analyzed to achieve high-dynamic performance in load regulation characteristics for robotic applications. The MIMO system transfer function of PMSM drive system incase of closed loop including the current control loop is used as the reference model. The simulation of pulse width modulated (PWM) inverter fed PMSM Controlled by MIMO fuzzy controller at closed loop is present.

Keywords: MIMO Fuzzy control, neural network, PMSM and inverter.

1. Introduction

For a long time, permanent magnet synchronous motors (PMSM) applied in some particular application fields, e.g. for servo drives. However, in the recent years PMSMs gained increasing importance in novel domains like in automotive hybrid drive trains or wind power plants as a result of powerful rare earth magnets. Characteristic of these new applications is the borderline design to aim for highest utilization of torque and power. The behaviour of these motors may differ considerably from the well known servo motor.

The most commonly used method of control for PMSM is field oriented control (FOC) [1]. The FOC represents the attempt to reproduce, for a PMSM, a dynamical behaviour similar to that of the dc machine, characterized by the fact that developed torque is proportional to the modulus of the stator current: to reach this objective, it is necessary to keep the rotor flux value constantly equal to the nominal value, so that, contemporarily, the optimal magnetic circuits exploitation guarantees the maximum power efficiency, [2-3]. Regulation of currents i_d and i_q in closed loops leads indirectly to control of the motor developed torque.

Recently, several control techniques have been developed for improving the performance of the PMSM drives. Many researches have been carried out to apply Fuzzy Logic to the control of PMSM drive system to deal with the nonlinearities and uncertainties of the dynamic model of PMSM, [4].

2. MIMO System

The majority of process industries are nonlinear, Multi-Input Multi-Output (MIMO) systems. The control of these systems is met with a number of difficulties due to process interactions, dead time and process nonlinearities. The difference between MIMO systems control and single-input single-output (SISO) systems control is based on an estimation and compensation of the process interaction among each degree of freedom. It is obvious that the difficulty of MIMO systems control is how to overcome the coupling effects among each degree of freedom. To obtain good performance, coupling effect cannot be neglected. Hence SISO system control scheme is not easy to implement on complicated MIMO systems. In addition, the control rules and controller computation will grow exponentially with respect to a number of considered variables. Therefore, intelligent control strategy is gradually drawing attention.

The MIMO systems usually possess characteristics of nonlinear dynamics coupling, [5-7]. Therefore, the difficulty of MIMO systems control is how to overcome the coupling effects among each degree of freedom [5]. The structure of the MIMO controller can be divided into multi-input single output (MISO) and SISO controllers. Each MIMO controller then consists of many fuzzy logic controllers (FLC). It is clear that the control structure of the fuzzy control (FC) system is very complicated when the input variable is multi-degree and the output variable is one degree, or more than one degree. These parameters

of a FC system are not easily decided because FC rules will be grow as a geometric series, and much computing time will be required. To minimize the amount of memory used and computational time, we can put constraints on the type of fuzzy controller (e.g., membership functions) or limit the rules. But it will affect the performance of the system; hence we need the solution which exhibits good performance with smallest possible rule base.

In this paper, a neural network (NN) tuned fuzzy controller is designed for MIMO systems from the given set of input output data. An appropriate coupling tuned fuzzy controller is incorporated to control the MIMO systems to compensate for the dynamics coupling among each degree of freedom. A tuned fuzzy controller is obtained from data set in two steps. First, the data set is partitioned into a set of clusters based on the similarity of data. Then using subtractive clustering algorithm a fuzzy if-then rule is extracted from each cluster to form a fuzzy rule base. Secondly, a fuzzy NN is designed accordingly to optimize the parameters of the fuzzy system. After simulation of a two-level mass–spring MIMO system and performed through the PWM inverter, which feeds the PMSM, which will be done experimentally.

3. Basic Modeling of the Drive for Dynamic Performance

The drive has been modeled for the design and simulation of the control. For the simulation the focus is put on the characteristics of the machine and the control. The converter has minor influence and is nearly neglected, acting as a controlled source of variable sinusoidal voltage with its typical delay time.

The drive, based on the machine, is modeled using space vectors [8]. Equations (1) to (3) show the stator voltages and the electromagnetic torque, given here in the rotor fixed reference frame:

$$V_{Sq} = R_S i_{Sq} + L_{Sq} \frac{d}{dt} i_{Sq} + \omega_m (L_S i_{Sd} + \psi_F) \qquad (1)$$

$$V_{Sd} = R_S i_{Sd} + L_{Sq} \frac{d}{dt} i_{Sd} - \omega_m L_{Sq} i_{Sq} \qquad (2)$$

$$T = \frac{3}{2} P(\psi_F i_{Sq} + (L_{Sd} - L_{Sq}) i_{Sq} i_{sd}) \qquad (3)$$

The relationship between torque and speed is given by
$$\omega_r = [(\mathbf{P}/2)/(Jp + B_m)].(T_e - T_L) \qquad (4)$$

It may be recall that ω_r is in electrical rad/sec and J is the total inertia of the rotor and connected load.

Because of the constant flux Ψ_F in the machine, we get simple voltage equations (1), (2) compared for example to the induction machine. We can see the coupling of the d- and q-component of the stator current i_S to both components of the stator voltage V_S. Because of this, we have to compensate their influence for decoupled current control. The torque equation (3) is relative complex in the case of magnetic asymmetry ($L_{Sd} \neq L_{Sq}$). It simplifies for example, when i_{Sd} is controlled to zero, to a proportionality of torque and the q-component of the current.

4. Controller Structure For MIMO System

Fuzzy set theory and NN has been successfully applied in a number of control applications [9-12] based on the SISO system point of view without system model consideration. In this paper, FC strategy is used to control MIMO systems. The block diagram of the MIMO FC scheme is shown in Fig. 1.
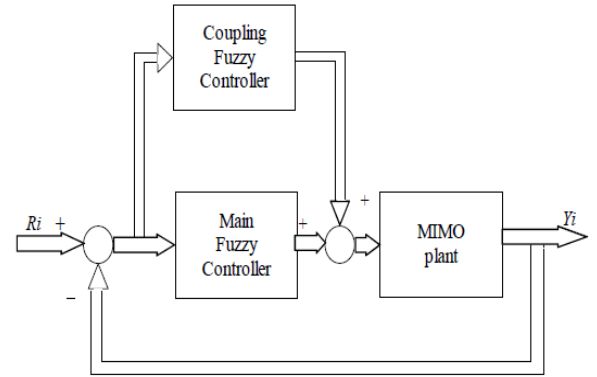

Fig. 1, Block diagram of the MIMO fuzzy control scheme.

The design procedure of the FC strategy is used to control each degree of freedom of this MIMO system individually. Then, an appropriate coupling fuzzy controller is designed to compensate for the coupling effects of system dynamics among each degree of freedom.

An ordinary fuzzy controller that usually operates with system output error and error change was chosen as the main controller to control each degree of freedom of the MIMO systems. Here, the input variables of the conventional fuzzy controller for among each degree of freedom of a MIMO system were defined individually as

$$e_i(k) = R_i(k) - Y_i(k) \qquad (5)$$
$$\Delta e_i(k) = e_i(k) - e_i(k-1) \qquad (6)$$

Where $e_i(k)$ is the position error of the ith degree,

$\Delta e_i(k)$ is used for change in error of the ith degree,

$R_i(k)$ is the reference input of the ith degree

and $Y_i(k)$ represents the ith position output of each degree of freedom of this MIMO system at the kth sample.

The relationship between the scaling factors (SFs) (G_e, $G_{\Delta e}$, G_u) are the input and output variables of the FLC is

$$e_{iN} = G_e \times e_i,$$
$$\Delta e_{iN} = G_{\Delta e} \times \Delta e_i, \qquad\qquad (7)$$
$$\Delta u_i = G_{\Delta u} \times \Delta u_{iN}$$

Selection of suitable values for G_e, $G_{\Delta e}$ and G_u are made based on the knowledge about the process to be controlled and sometimes through trial and error to achieve the best possible control performance. This is so because, unlike conventional nonfuzzy controllers to date, there is no well-defined method for good setting of SF's for FLC's. The SFs are the significant parameters of FLC because changing the SFs changes the normalized universe of discourse, the domains, and the membership functions (MFs) of input/output variables of FLC.

All MFs for controller inputs (i.e., e_i and Δe_i) and incremental change in controller output (i.e., Δu_i) are defined on the common normalized domain [-1,1]. We use symmetric triangles (except the two MFs at the extreme ends) with equal base and 50% overlap with neighboring MFs as shown in Fig. 2. This is the most natural and unbiased choice for MFs.
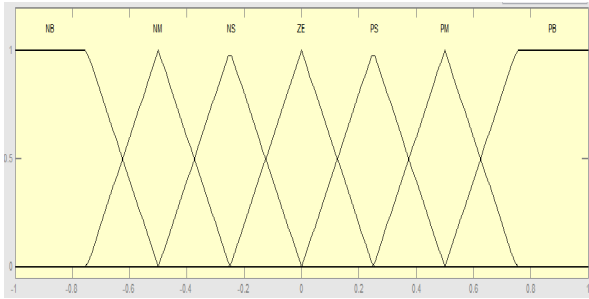

Fig. 2 MFs for e_i, Δe_i and Δu_i

The above design process, the actual control input voltage for the main fuzzy controller can be written as
$$u_i(k) = u_i(k-1) + \Delta u_i(k) \qquad\qquad (8)$$
In (8), k is the sampling instant and $\Delta u_i(k)$ is the incremental change in controller output, which is determined by the rules of the form If e_i is E_i and Δe_i is ΔE_i, then Δu_i is ΔU_i. The rule base for computing is a standard one [10] as shown in Table 1.

The FC rules of the coupling fuzzy controller are similar to the main fuzzy controller. The output of the coupling fuzzy controller is chosen directly as the coupling control input voltage. The main reason is that

there is a different coupling effect for each sampling interval and it does not have an accumulating feature. The coupling effect is incorporated into the main fuzzy controller for each step to improve system performance and robustness.

Table 1, Rule base

$\Delta e_i/e_i$	NB	NM	NS	ZE	PS	PM	PB
NM	NB	NB	NB	NM	NS	NS	ZE
NM	NB	NM	NM	NM	NS	ZE	PS
NS	NB	NM	NS	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PS	PM	PB
PM	NS	ZE	PS	PM	PM	PM	PB
PB	ZE	PS	PS	PM	PB	PB	PB

Therefore, the total control input voltage of the MIMO fuzzy controller is represented as
$$U_i(k) = u_i(k) + U(k)_{i \to l} \qquad , i \neq l \qquad (9)$$
where $u_i(k)$ expresses the system control input voltage of the ith degree of a main fuzzy controller. $U(k)_{i \to l}$ represents the coupling effect control of the lth degree relative to the ith degree of the coupling fuzzy controller.

Since the additional coupling fuzzy controller is introduced to compensate the unknown coupling effects of MIMO systems, the control strategy presented here should be employed to control any complicated MIMO systems. Therefore, the application of this control strategy is not constrained to a specific MIMO control system. In order to evaluate the control performance of a fuzzy controller for MIMO control systems, a two-level mass–spring MIMO system is considered [13]. The vibration system is reproduced as

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -\dfrac{(K_1+K_2)}{M_1} & -\dfrac{(B_1+B_2)}{M_1} & \dfrac{K_2}{M_1} & \dfrac{B_2}{M_1} \\ 0 & 0 & 0 & 1 \\ \dfrac{K_2}{M_2} & \dfrac{B_2}{M_2} & -\dfrac{K_2}{M_2} & -\dfrac{B_2}{M_2} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ \dfrac{\Omega}{M_1} & 0 \\ 0 & 0 \\ 0 & \dfrac{\Omega}{M_2} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} + \begin{bmatrix} 0 \\ \dfrac{d_1}{M_1} \\ 0 \\ \dfrac{d_2}{M_2} \end{bmatrix}$$

$$\begin{bmatrix} Y_1(k) \\ Y_2(k) \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

where x_1 and x_3 are the displacements of the main and secondary masses M_1 and M_2,

x_2 and x_4 are the velocities of the mass M_1 and M_2,
B_1 and B_2 are the damping coefficients of the main system and the secondary system,
u_1 and u_2 are the inputs,
Ω is a constant,
d_1 and d_2 are the disturbance forces applied to the main and the secondary systems,
$Y_1(k)$ and $Y_2(k)$ are the displacement of the first mass and second mass.

The structure of the FC scheme to control this MIMO active vibration system is shown in Fig. 3. The input variables of the fuzzy controller are defined same as in (8) and (9) when indices i=1; 2 represent the main mass and second mass, respectively.

$$u_1(k) = u_1(k\text{-}1) + \Delta u_1(k)$$
$$u_2(k) = u_2(k\text{-}1) + \Delta u_2(k) \qquad (10)$$
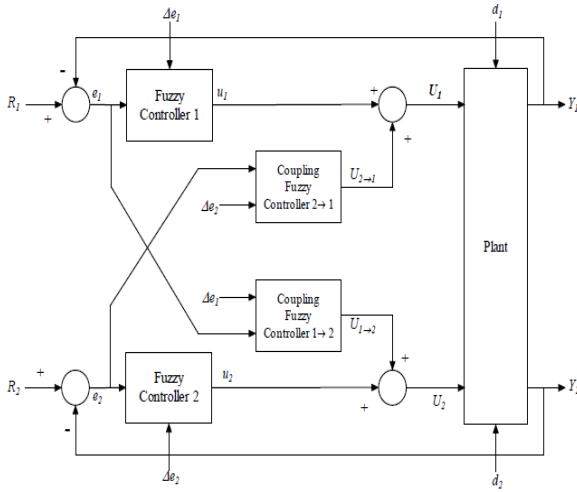
Fig. 3, Structure of the MIMO fuzzy control scheme

And the total control input voltage of this plant is represented as

$$U_1(k) = u_1(k) + U(k)_{2\to1}$$
$$U_2(k) = u_2(k) + U(k)_{1\to2} \qquad (11)$$

where $u_1(k)$ and $u_2(k)$ indicate the voltage increment of the first mass and the second mass on the k step sampling interval, respectively; $u_1(k)$ and $u_1(k-1)$ express the system control input of the first mass on the k step and $k-1$ step sampling intervals, respectively. Similarly, $u_2(k)$ and $u_2(k-1)$ are used for expressing the system control input of the second mass on the k step and $k-1$ step sampling intervals, respectively. $U(k)_{1\to2}$ and $U(k)_{2\to1}$ represent the coupling effect control of the first mass relative to the second mass and the second mass relative to the first mass of the coupling fuzzy controller, respectively.

5. Design of Fuzzy Neural Netwok

The neurofuzzy learning scheme is mainly composed of two steps. In the first step, the number of rules nodes (hence the structure of the network) and initial rule parameters (weights) are determined using structure identification; in the latter all parameters are adjusted using parameter identification as shown in Fig 4.

To initiate the structure tuning, a training set composed of input-output data which contains n inputs and one output must be provided. Without loss of generality, we assume that the data points have been normalized in each dimension so that they are bounded by a unit hypercube. We consider each data point as a possible cluster center and define a measure of the potential of data point as discussed in [14]. To extract the set of initial fuzzy rules, firstly data is separated into groups according to their respective classes. Subtractive clustering is then applied to the input space of each group of data individually for identifying each class of data. Each cluster center may be translated into a fuzzy rule for identifying the class.
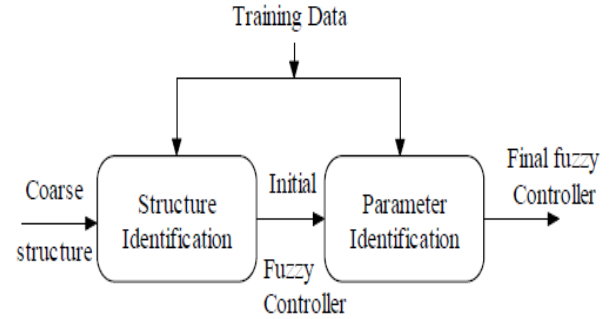

Fig. 4, Steps for neurofuzzy learning.

One can also write this rule in the more familiar form:
Rule i: If X_1 is A_{i1} & X_2 is A_{i2} &... then class is c_1.

Where X_j is the j'th input feature and A_{ij} is the membership function (Gaussian type) in the i'th rule associated with the j'th input feature.

The membership function A_{ij} is given by

$$A_{ij}(X_i) = \exp\left\{ -\left(\frac{X_j - m_{ij}}{\sigma_{ij}} \right)^2 \right\} \qquad (12)$$

Where m_{ij} is mean and σ_{ij} is deviation.

In parameter identification, the NN techniques are used to refine the parameters of the initial fuzzy rules. A NN with three layers is designed based on the fuzzy rules obtained in first phase. To realize the described fuzzy inference mechanism, the operation of a NN is shown in Fig 5 and described below:

Layer 1: Units in this layer receives the input value $(X_1, X_2, \ldots, X_n)$ and acts as the fuzzy sets representing the corresponding input variable. Nodes in this layer are arranged into j groups; each group representing the IF-part of a fuzzy rule. Node (i, j) of this layer produces its output $O_{ij}^{(1)}$, by computing the corresponding Gaussian membership function:
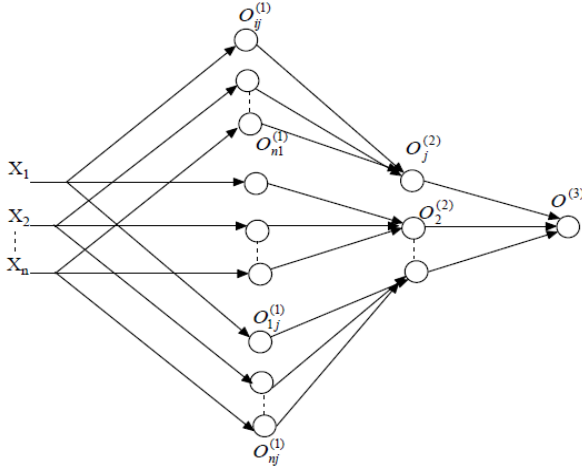

Fig. 5, Architecture of fuzzy neural network.

$$O_{ij}^{(1)} = A_{ij}(X_j) \qquad (13)$$

Layer 2: The number of nodes in this layer is equal to the number of fuzzy rules. A node in this layer represents a fuzzy rule; for each node, there are n fixed links from the input term nodes representing the IF-part of the fuzzy rule. Node $O_j^{(2)}$ of this performs the AND operation by product of all its inputs from layer 1. For instance,

$$O_j^{(2)} = \prod_{i=1}^{n} O_{ij}^1 \qquad (14)$$

Layer 3: This layer contains only one node whose output $O^{(3)}$ represents the result of centroid defuzzification, i.e.,

$$O^{(3)} = \frac{\sum_{j=1}^{J} O_j^2 c_j}{\sum_{j=1}^{J} O_j^2} \qquad (15)$$

Here c_j is the class of data as discussed above and it is also called the fuzzy singletons defined on output variables. Apparently, m_{ij}, σ_{ij} and c_j are the parameters that can be tuned to improve the performance of the system. After that a hybrid learning algorithm which combines gradient descent and least square estimator method is used to refine these parameters. Each epoch of

the hybrid learning procedure is composed of a forward pass and backward pass. In the forward pass, input data is supplied and functional signals go forward to calculate each node output. The consequent parameters are identified by least square estimator method. After identifying the parameters, the functional signals keep going forward till the error measure is calculated. In the backward pass, the error rates (derivative of the error measure w.r.t. each node output) propagate from the output end towards the input and the premise parameters are updated by gradient method. The details of Hybrid learning algorithm is given by Jang in [15] and we are using the same procedure.

6. Simulation Results of the System

Actually we begin by measuring the error between the actual speed and current (which should be contro1led) and the reference speed matching the torque command. This controlled speed gives us a good indication about the volt, which must apply to the motor. Fig. 6 shows the block diagram of the system.
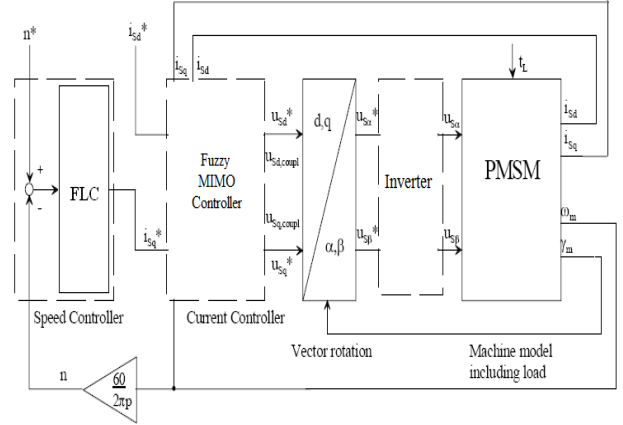

Fig. 6, Block diagram of the system.

This section presents a computer simulation of the proposed control scheme for a 0.8 kW PMSM using Fuzzy MIMO controller. The motor specifications and parameters are given in Appendix. The dynamic performance of the drive system for different operating conditions has been studied with the application of Fuzzy MIMO controller. Several tests were performed to evaluate the performance of the proposed system. Figure 7 shows the inverter's Simulink model. One switch per phase is used to set Vdc or –Vdc on the phase. As an activation signal for each switch is used the PWM. While, Fig. 8 is shown simulink model of the PMSM, [16].
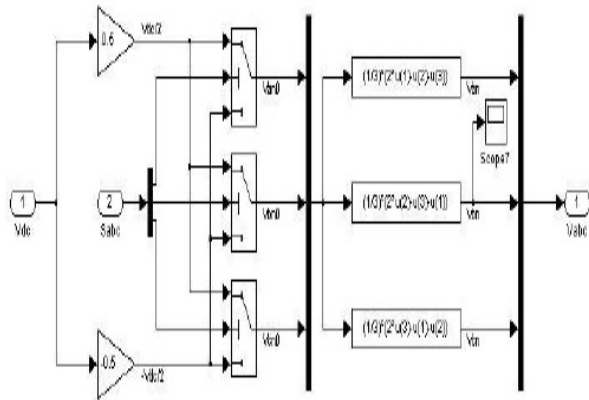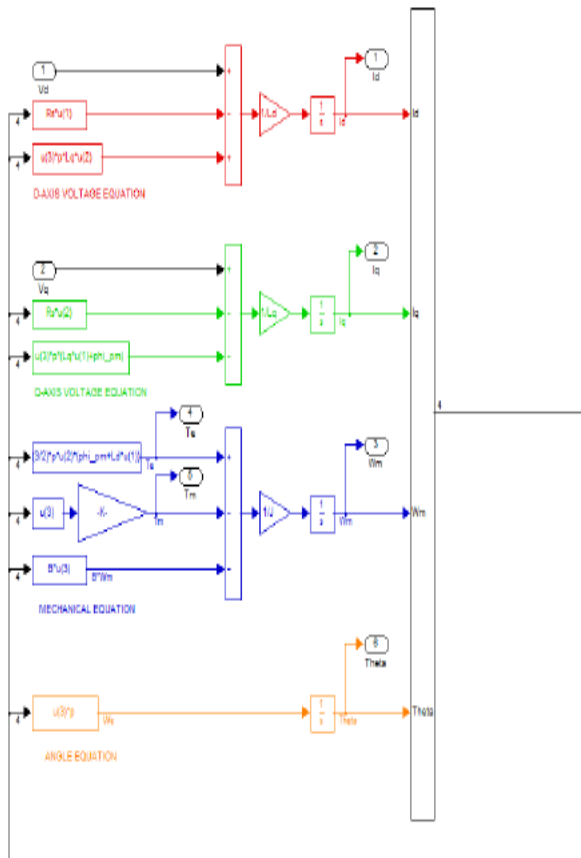
Fig. 7, Simulink model of the inverter.

Fig. 8, Simulink model of the PMSM.

Figure 9 shows the speed response of the system due to a step change in the command. While, Fig. 10 shows an important issue of the electrical drives is the capability to reject the effects of load disturbance. Figure 10 (a) presents the overall responses of the speed the load torque and the phase current. The system started at Load

then at t =0.3sec the load torque is decreased to 50% of the full load and at t =0.5sec it is increased from 50% to 75% of the full load torque. Figure 10 (b-c) shows the responses of the speed, load torque and current during the sudden step in the load torque from start to 100% load then to 50% load and change to 75% load. While, Fig. 11 shows the rotor position waveform. This reveals that the performance of the overall system is robust to the load disturbances. Computer simulation results demonstrate that proposed Fuzzy MIMO controller obtain robust response for the drive system.
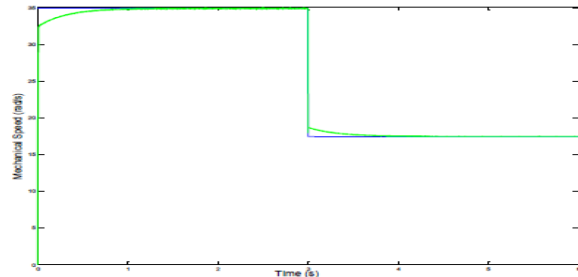

Fig. 9, Mechanical speed (Ref. in blue, Actual in green).

7. Conclusion

In this paper, a NN tuned fuzzy Controller for controlling multi inputs multi outputs (MIMO) systems for PMSM drive system has been presented. The MIMO fuzzy controller with derivative action can achieve much better results than the conventional FLC. Thus the control structure is simple and design process is easier and applied to PMSM drive system. In spite of the simple structure of MIMO fuzzy controller speed controller, the obtained results show that those controllers can provide a fast and accurate dynamic response in tracking and disturbance rejection characteristics under load torque variations. At the same time, a reduction of the computation time of rules base has been occurred as a result of the simple construction of the MIMO fuzzy controller. The overall system performance has been investigated at different dynamic operating conditions. It is concluded that the proposed MIMO fuzzy controller shown superior performances and robust stability despite the presence of external load disturbances.
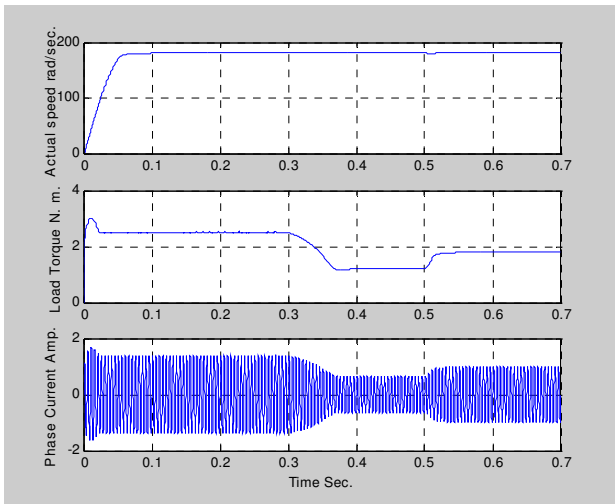
Appendix:

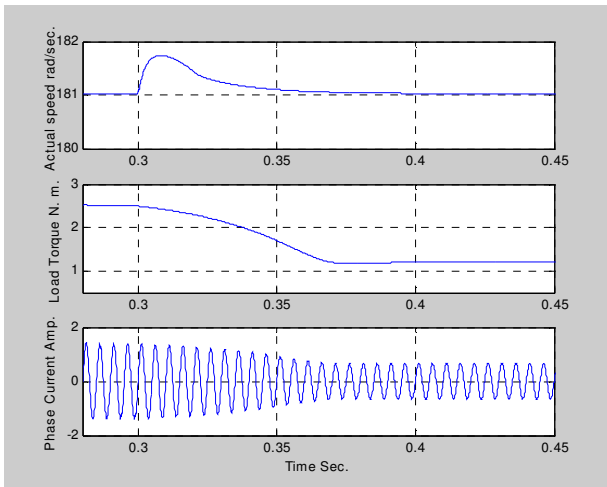Machine parameters: PMSM,
460V, 8-poles,
Resistance/ph $= 1.2\Omega$,
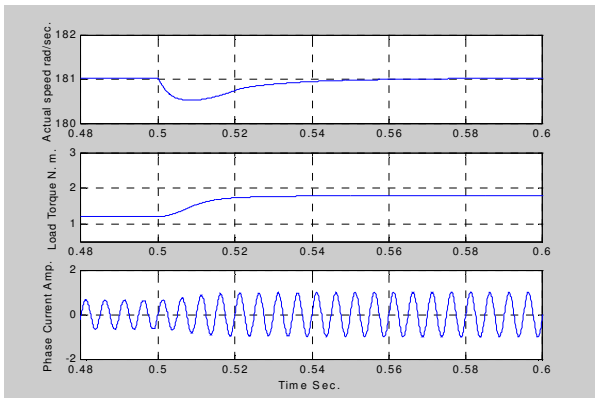self inductance/ph=8.7 mH,

$J = 0.000133$ kg.m^2 ,
$\beta = 0.00002935$ N.m/rad/sec

(a) Overall waveforms during sudden changes.

(b) From 100% to 50% load.

(c) From 50% to 75% load.
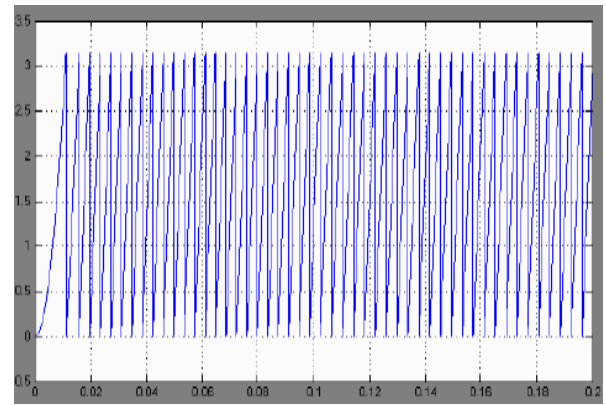Fig. 10, Speed, load torque, and phase current during sudden changes in load torque.

Fig. 11, Rotor position waveform.

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