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Comparative Analysis of Intelligent Controllers for Permanent Magnet Synchronous Motor Drive Systems

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Abstract: The PMSM (Permanent Magnet Synchronous Motor) drive systems are often used in electrical drives because of their simple structures, ease of maintenance and efficiency. However, the nonlinear behaviour which arises mainly from motor dynamics and load characteristics and the presence of uncertainties make their control an extremely difficult task. So, the speed control strategy should be adaptive and robust for successful industrial applications. To handle the control issue more effectively, three artificial intelligence control strategies namely, Fuzzy Logic (FL), Artificial Neural Network (ANN) and Neuro-Fuzzy (NF) are proposed since they require only a reduced computation power, while maintaining satisfactory static and dynamic performance and a good insensitivity to perturbations and parameter uncertainties. The traditional back-propagation learning algorithm is used for training the ANN and the NF controllers. The performances of the three control strategies are investigated and compared in simulation. The results show that the intelligent controllers are reliable and highly effective in the speed control of the PMSM.

Key words: Speed control, fuzzy logic controller, artificial neural network controller, neuro-fuzzy controller, PI controller, vector control, permanent magnet synchronous motor

INTRODUCTION

Among AC drives, the permanent magnet synchronous motor has been becoming popular due to some of its advantageous features (Krause, 1986). In high performance variable speed drive (HPVSD) systems the motor speed should closely follow a specified reference trajectory regardless of load disturbances, parameter variations and model uncertainties. In order to achieve high performance, field oriented control is the most popular choice. Traditionally, these control issues are handled by the conventional Proportional-Integral (PI) controller and other controllers such as model reference adaptive controller, sliding mode controller, variable structure controllers. However, the difficulties of obtaining the exact d-q axis reactance parameters of the PMSM lead to cumbersome design approach for these controllers (Liu *et al*., 1988). Moreover, the conventional fixed gain PI controller is very sensitive to step change of control speed, parameter variations and load disturbances (Novotny and Lorenz, 1986). Moreover, the precise speed control of a PMSM drive becomes a complex issue due to nonlinear coupling among its winding currents and the rotor speed as well as the nonlinearity present in the electromagnetic developed torque due to magnetic saturation of the rotor core. Thus, the intelligent controllers are expected to play an increasing role for high performance PMSM drive systems.

Recently, researchers (Ibrahiin and Levi, 2002; Uddin and Rehman, 2000; Rehman *et al*., 2002; Udin *et al*., 2002; Rehman and Hoque, 1998; Elbuluk *et al*., 2002; Singth *et al*., 1998; Bolognain and Zigliono, 1996; El-Sarkawi *et al*., 1994) have done extensive research for application of Fuzzy Logic Controller (FLC), Artificial Neural Network (ANN) and Neuro-Fuzzy (NF) controllers in HPVSD systems. Simplicity and less intensive mathematical design requirements are the main features of intelligent controllers, which are suitable to deal with nonlinearities and uncertainties of electric motors. However, each intelligent control algorithm has its own merits and drawbacks (Zilochian and Jamshidi, 2001). Therefore, the main objective of this study is to provide a useful comparison among various intelligent controllers such as FLC, ANN and NF controllers in terms of design, implementation and performance aspects for Permanent Magnet Synchronous Motor (PMSM) drives. As a representative of ANN, a standard Multi-layer Neural Network (MLP) is used in this study. For the Fuzzy Logic Controller (FLC), the neuronal implementation allows the adjustment of the various membership functions. For the scope of the comparison, a closed loop vector control scheme for the PMSM incorporating the intelligent controllers is successfully implemented and the performances are investigated and compared in simulation at different operating conditions.

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Background: The earliest vector control principles for AC permanent magnet synchronous machines resembled the control of a fully compensated DC machine. The idea was to control the current of the machine in a quadrature space, denoted q-space, with the magnetic flux created by the permanent magnets. The torque is then directly proportional to the product of the flux linkage created by the magnets and the current. In an AC machine the rotation of the rotor demands that the flux must rotate at a certain frequency. If the current is then controlled in q-space with the flux, the current must be an AC in contrast with the DC current of a DC machine. The mathematical modelling of an AC synchronous machine is most conveniently done using a coordinate system, which rotates synchronously with the magnetic axis of the rotor, i.e. with the rotor. The x-axis of this coordinate system is called the direct axis (usually denoted as 'd') and the y-axis is the quadrature axis (denoted as 'q'). The magnet flux lies on the d-axis and if the current is controlled in q-space with the magnet flux it is aligned with the q-axis. This type of control is referred to as id-0-control.

A PMSM motor consists of permanent magnets mounted on the rotor surface and three phase stator windings which have a sinusoidal distribution and displaced by 120°. The stator voltage equations of a PMSM in the rotor reference frame (q-d frame) are described as follows:

$$v_q = R_a i_q + L_q \dot{i}_q + L_d P w_r i_d + \lambda_m w_r \tag{1}$$

$$v_d = R_a i_d + L_d \dot{i}_d - L_q P w_r i_q \tag{2}$$

$$Te = 1.5[\lambda_m i_q + (L_d - L_q) i_d i_q] \tag{3}$$

$$w_r = \theta \tag{4}$$

$$w_r = \frac{1}{J}(T_e - F w_r - T_m) \tag{5}$$

From Eq. 1 and 2, the discrete-time equation can be obtained as follows:

$$v_q(k) = R_a i_q(k) + \frac{L_q}{T}\left[i_q(k+1) - i_q(k)\right] + L_d P w_r i_d(k) + \lambda_m w_r \tag{6}$$

$$v_d(k) = R_s i_d(k) + \frac{L_d}{T}\left[i_d(k+1) - i_d(k)\right] - L_q P w_r i_q(k) \tag{7}$$

$$Te(k) = \lambda_m i_q(k) + P\left(L_d - L_q\right) i_d(k) i_q(k) \tag{8}$$

Where R_a : Resistance of the stator windings, i_d, i_q: d and q axis currents; L_d, L_q: d and q axis inductances; w_r: angular velocity of the rotor; θ: Rotor angular position; λ_m: amplitude of the flux induced by the permanent magnets of the rotor in the stator phases.

T_e: Electromagnetic torque; T_m: Shaft mechanical torque; P: Number of pole pairs.

J: Combined inertia of rotor and load; F: Combined viscous friction of rotor and load.

One meets primarily two methods for implementation of the strategy of control which consists in maintaining the current id with a zero value and to control speed and/or the position with acting on the current i_q, i.e. on the couple developed by the engine. The first consists in controlling the alternating currents circulating in the stator windings of the machine, the second to control the Park's components of these currents (Krause, 1986).

Control principle: The machine parameters are given in Table 1. A typical closed loop vector control scheme for PMSM is shown in Fig. 1 in which different intelligent controllers are used as speed controller. From the speed reference and measured speed, a regulator calculates the set point of the torque, i.e., the value of reference of the current i_q. The rotor position measured by a position encoder, combined with the reference values i_d and i_q allow to calculate, by a reverse Park's transformation, the reference values of currents i_a*, i_b*, i_c*. These values are compared with the measured values i_a, i_b, i_c to fix the

Table 1: The machine parameters

Pairs of poles P	4
Stator resistance	2.875 Ω
Flux induced by magnets	0.175 Wb
Inductance Ld	8.5 mH
Inductance	Lq8.5 mH

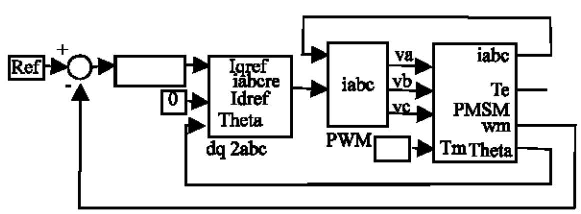


Fig. 1 : Vector control with local current loops

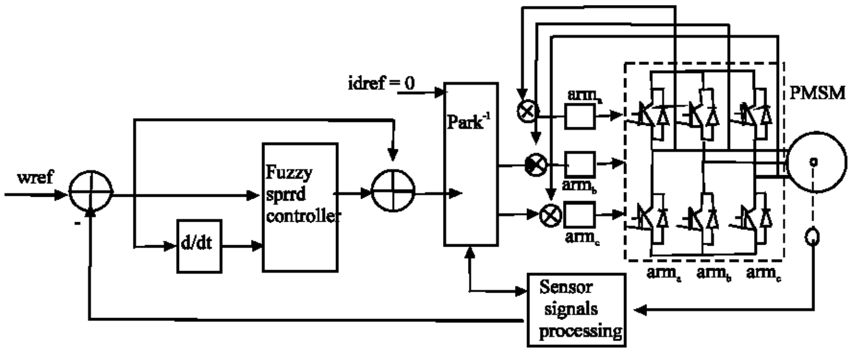
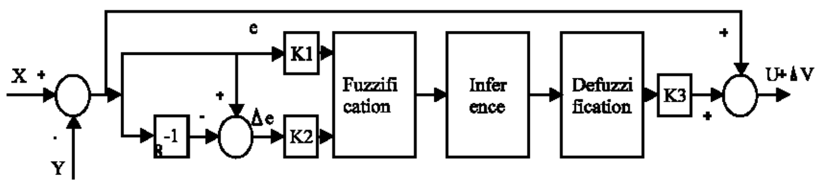


Fig. 2: Vector control with fuzzy inverse model controller



$$e(k) = x(k) - y(k) = \Delta\omega$$
$$\Delta e(k) = e(k) - e(k-1) = \Delta\omega$$

Fig. 3: Structure of the controller

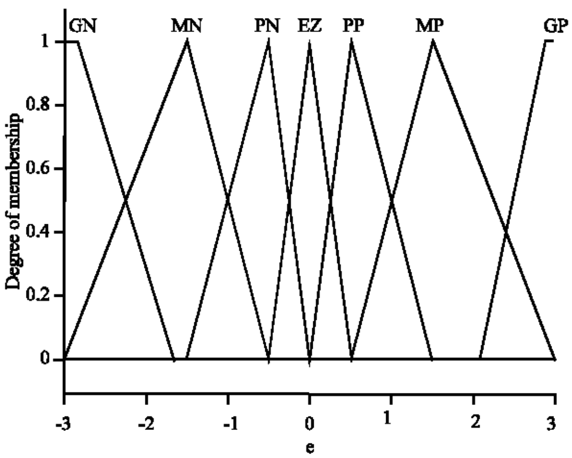


Fig. 4: FLC Membership functions for the input *e*

control signals of each inverter's arm. These signals are obtained either by regulators with threshold, or by analog PI regulators whose output feeds a modulator MLI (Leonhand, 1985; Lajoie-Mazenc *et al.*, 1985; Matagne, 1993) .

PID controller: Despite the impressive advances achieved in the control engineering discipline, PID still remains the most common control algorithm in industrial use today. It is widely used because of its versatility, high reliability and ease of operation (Astron and Hagglund, 1995). A standard method of setting the parameters is through the use of Ziegler-Nichols' tuning rules (Ziegler and Nichols, 1942). These techniques were developed empirically through the simulation of a large number of process systems to provide a simple rule. The methods operate particularly well for simple systems and those which exhibit a clearly dominant pole-pair, but for more complex systems the PID gains may be strongly coupled in a less predictable way. For these systems, adequate performance is often only achieved through manual and heuristic parameter variation.

FLC scheme: Unlike the classical control design, which requires a plant model for designing the controller, fuzzy logic incorporates an alternative way which allows one to design a controller using a higher level of abstraction without knowing the plant model. This makes Fuzzy Logic Controller (FLC) very attractive for ill-defined systems or systems with uncertain parameters (Zaden, 1973). In order to design the FLC, some variables representing the dynamic performance of the system, should be chosen to be fed as the inputs. In addition to the proper input signals, signal gains and fuzzy subsets should be defined.

Table 2: Fuzzy inference rules

e Δe	GN	MN	PN	EZ	PP	MP	GP
GP	EZ	PP	MP	GP	GP	GP	GP
MP	PN	EZ	PP	MP	GP	GP	GP
PP	MN	PN	EZ	PP	MP	GP	GP
EZ	GN	MN	PN	EZ	PP	MP	GP
PN	GN	GN	MN	PN	EZ	PP	MP
MN	GN	GN	GN	MN	PN	EZ	PP
GN	GN	GN	GN	GN	MN	PN	EZ

Fig. 5: FLC output characteristics

It is common to use the output error and the rate derivative of the output as controller inputs (Lown, 1997; Talaq and Al-Basir, 1999). In this study, the motor speed deviation($\Delta\omega$), its derivative ($\Delta\dot{\omega}$) and the acceleration, are considered as the inputs of the FLC Fig. 2. After and signals pass through two appropriate gains or scaling factors and then are fed to the FLC. The output ΔI_q of the controller is also scaled by passing through the output gain, Fig. 3. To convert the measured input variables of the FLC into suitable linguistic variables, seven fuzzy subsets are chosen. The membership functions of these subsets have trapezoidal and triangular shape. Fig. 4 shows the membership functions. In this paper, both inputs of the FLC have seven subsets. Thus, one fuzzy rule Table with forty-nine rules is constructed Table 2. Fig. 5 illustrates the control surface. The center of gravity method is employed.

The values of the constants, membership functions, fuzzy sets for the input/output variables and the rules used in this work are selected by trial and error to obtain the optimum drive performance.

Neural networks scheme: The single output of a two-layer NN with a linear output activation function is given by:

$$y_{NN} = \sum_{j=1}^{N_h} v_j \sigma\left(\sum_{k=1}^{N_i} w_{jk}.\varphi_k + \theta_{wj} \right) + \theta_v \qquad (9)$$

where $\varphi_1,\ldots,\varphi_{N_i}$ are the NN inputs, $\sigma(.)$ is a sigmoid activation function, w_{jk} are input-to-hidden layer interconnection weights andv_j are hidden-to-output layer interconnection weighθ_v θ_{wm} m=1,2,... are bias. N_i and N_h are the numbers of neurons in the input and hidden layers, respectively (Fig. 6).

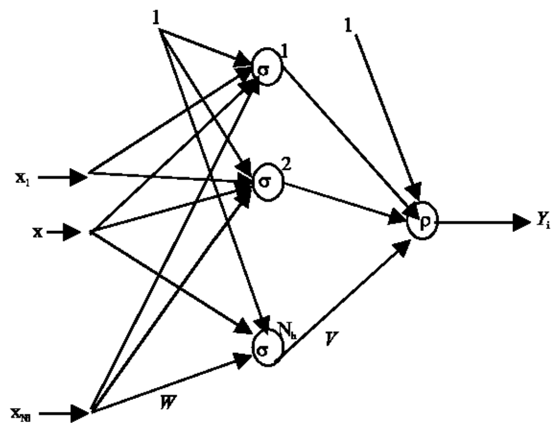


Fig. 6: Neural network

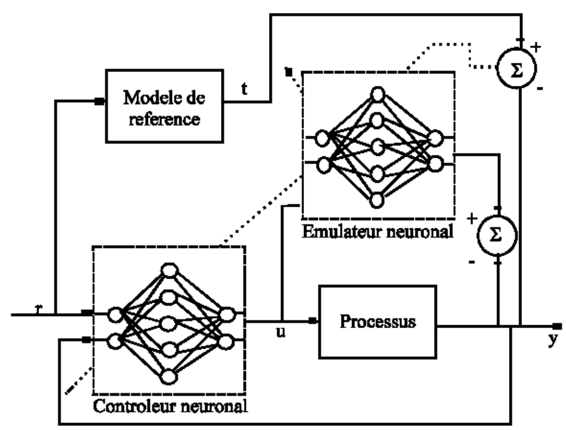


Fig. 7a: MRAC scheme for training the inverse controller

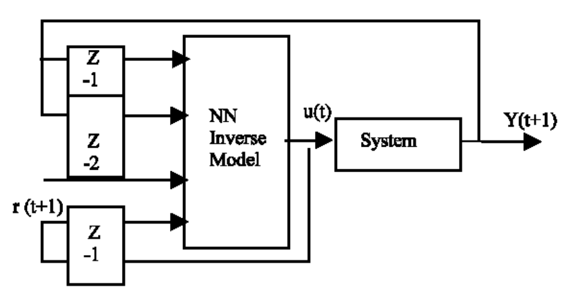


Fig. 7b: Scheme for inverse controller

Assuming that the system to be controlled can be described by:

$$y(t+1) = g\left[y(t),\ldots,y(t-n+1),u(t),\ldots u(t-m)\right] \quad (10)$$

We have trained off-line a direct neural network model of the system. Then we used the MRAC scheme (Fig. 7a) for the training of an inverse neural network model. This inverse model generates the control input $\hat{u}(t)$.

$$\hat{u}(t) = \hat{g}^{-1}\left[y(t+1),y(t),\ldots,y(t-n+1),u(t),\ldots u(t-m)\right]$$

It can be used for controlling the system by substituting in the expression of the control $\hat{u}(t)$ the output at time t+1 by the desired input reference r(t+1), Fig. 7b.

Anfis structure: Anfis (Adaptive-Network-based Fuzzy Inference System) has proven to be an excellent function approximation tool (Jang, 1993). Anfis implements a first order Takagi-Sugeno (TS) fuzzy system. The structure of this model is shown in Fig. 8. In this type of model, the condition part of a typical rule uses linguistic variables as

$$R^{(l)}(K)\text{: IF } (x_1 \text{ is } A_1^{(l)} \text{ and } x_2 \text{ is } A_2^{(l)}) \text{ THEN } y = w^{(l)} \quad (11)$$

Where l is the rule index and k denotes the kth numerical example.

The conclusion part is represented by a numerical value which is considered as a function of the system's condition expressed in the variables $x_1, x_2,\ldots x_m$, $A_j^{(l)}$ j =1, ...,m; l = 1,...,L . represent the fuzzy sets. These models are suitable for neural-based-learning techniques as gradient methods to extract the rules (Rahman *et al.*, 2002) and generate models with a reduced number of rules.

$$\omega^{(l)} = g(x_1, x_2, \ldots, x_m) \quad (12)$$

The neuro-fuzzy algorithm uses membership functions of triangular type in the present study. Fig. 8 illustrates the neuro-fuzzy scheme for an example with two inputs (x1=e, x2 = Δe) and one output variable (y =U). The information is propagated in three layers. In the first layer, the two inputs are codified into linguistic values by the set of triangular membership functions attributed to each variable. The second stage calculates to each rule R_l its respective activation degree. In the third layer, the inference mechanism weights each rule conclusion $\omega^{(l)}$, initialised by the cluster-based algorithm, using the activation degree computed in the second stage. The error

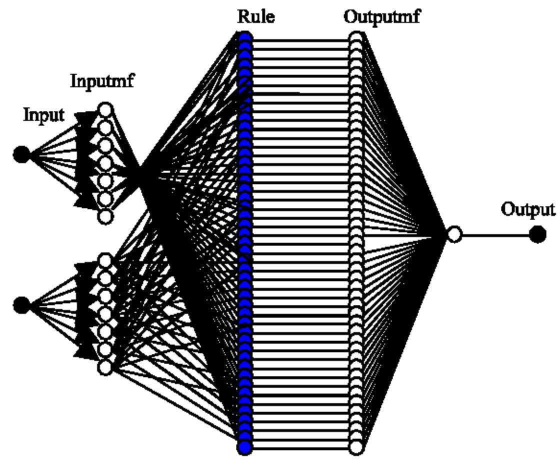


Fig. 8: Neuro-Fuzzy network

signal between the model inferred output value and the respective measured value (or teaching value) y_d, is used by the gradient descent method to adjust each rule conclusion. The algorithm changes the values of $\omega^{(l)}$ to minimize an objective function E usually expressed by the mean quadratic error (13). In this equation, the value y_d is the desired output value related with the condition vectorx(k) = $(x_1, x_2,\ldots,x_m)$. The element $\hat{y}^{(k)}$ is the inferred response to the same condition vector and computed by Eq. (14).

$$E = \frac{1}{2}\left(\hat{y}(x(k)) - y_d(k)\right)^2 \quad (13)$$

$$\hat{y}(x(k)) = \frac{\sum_{l=1}^{L}\prod_{j=1}^{m}\mu_{A_j^{(l)}}\left(x_j(k)\right)\omega^{(l)}(k)}{\sum_{l=1}^{L}\prod_{j=1}^{m}\mu_{A_j^{(l)}}\left(x_j(k)\right)} \quad (14)$$

Equation (15) establishes the adjustment rule of each conclusion by the gradient-descent method. The symbol η is the learning rate parameter and the index i denotes the number of learning iterations executed by the algorithm.

$$\omega^{(l)}(i+1) = \omega^{(l)}(i) - \eta\frac{\partial E}{\partial \omega^{(l)}} \quad (15)$$

The neuro-fuzzy control system: In the neuro-fuzzy control system, which is based on the feedback-error-learning scheme, each rule conclusion is modified by the gradient-descent method to minimise the Mean Squared Error (MSE) E. In the implemented controller, the neuro-fuzzy model minimises the mean

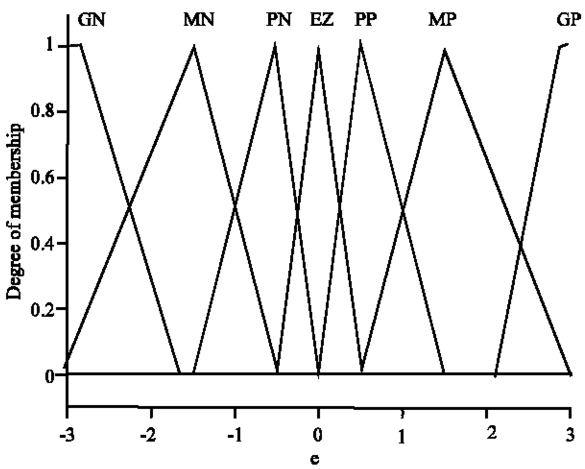


Fig. 9: NF Membership function for the input e

Fig. 10: NF output characteristics

squared error generated by the Proportional controller (P) to adjust each rule as indicated in Eq. 16.

$$\begin{cases} E = \frac{1}{2}\left(P(\hat{y} - y_d)^2\right) \\ \omega^{(l)}(i+1) = \omega^{(l)}(i) - \eta \frac{\partial E}{\partial \omega^{(l)}} \end{cases} \tag{16}$$

Figure 9 shows the membership functions where the inputs of the NF have seven subsets. Thus, one fuzzy rule Table with forty-nine rules is constructed (same as Table 2). Figure 10 illustrates the control surface.

RESULTS

A plant consisting of a three-phase permanent magnet synchronous machine with sinusoidal flux distribution rated 1.1 kW, 220 V, 3000 rpm is fed by a PWM inverter. The machine is modelled in the dq rotor

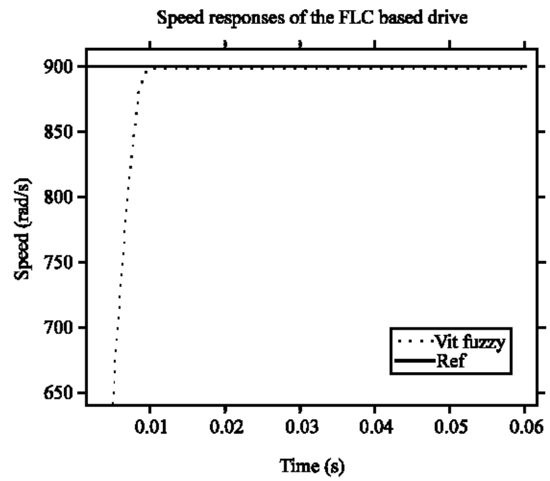


Fig. 11: Speed responses of the FLC based drive, with torque disturbance at 0.04s

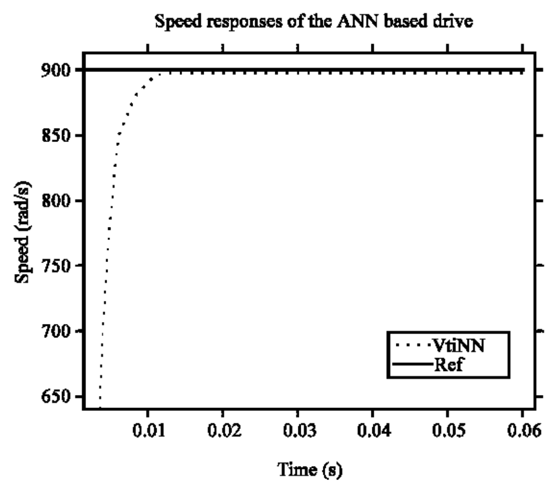


Fig. 12: Speed responses of the ANN based drive, with torque disturbance at 0.04s

frame the load torque applied to the machine's shaft is originally set to its nominal value (3 Nm) and steps down to *1 Nm at t=0.04 s.*

The simulated speed response of the PMSM drive system incorporating FLC is shown in Fig. 11. It is clear that the drive can follow the command speed without significant overshoot and undershoot and zero steady-state error. However, it is found that the motor suffers from vibration which is indicated by the spikes in speed response even at steady-state condition. For HPVSD (High Performance Variable Speed Drive) applications this is not acceptable. This chattering occurs due to switching of the rules of the FLC. Figure 12 shows the simulated speed response of the PMSM drive system

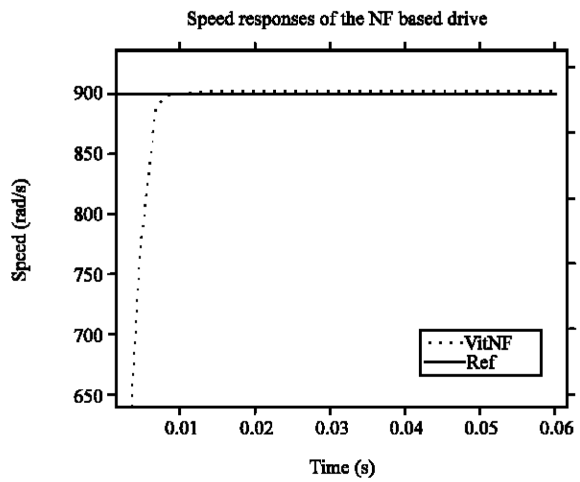


Fig. 13: Speed responses of the NF based drive, with torque disturbance at 0.04s based drive, with torque disturbance at 0.04s

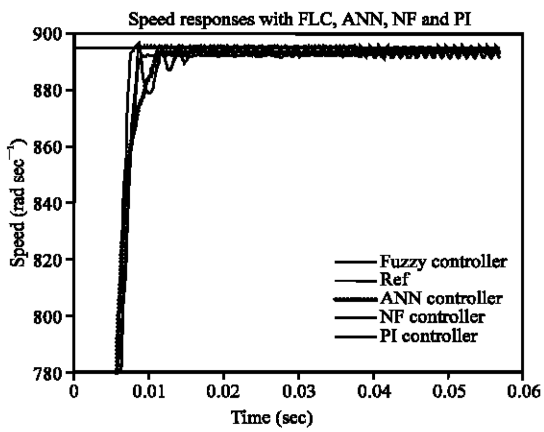


Fig. 14: Speed responses with FL, ANN, based drive, with torque disturbance at 0.04s NF and PI controllers, with torque change at 0.04s

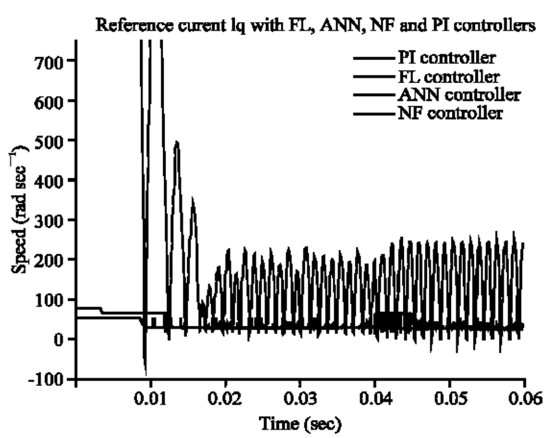


Fig. 15: Variation of reference current Iq, with FL, ANN, NF and PI controllers NF and PI controllers,

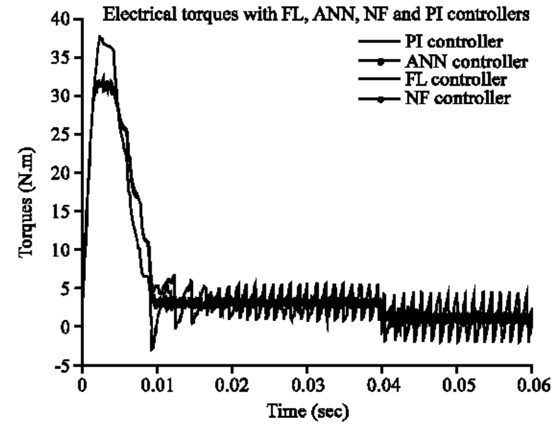


Fig. 16a: Electrical torques with FL, ANN,with torque change at 0.04s

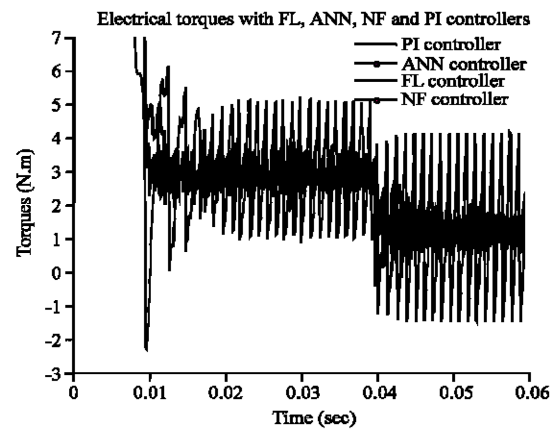


Fig. 16b: Electrical torques (Zoom)

incorporating ANN controller. It is shown that the drive response is similar to that of FLC but the speed response is faster and the vibration of the motor is also reduced as indicated by less spikes. Fig. 13 gives the simulated speed response of the PMSM drive systems incorporating NF controller. Clearly, it can be seen that the speed response is smoother than that of ANN but little more sluggish. To compare the above intelligent controllers with a conventional PI controller, the speed response, the variation of current I_q and torque are shown in Fig. 14, 15 and 16, respectively. Where we can see that with the PI controller the motor suffers from overshoot and chattering. This proves that the performance of intelligent controllers is more robust when compared to PI controller.

CONCLUSION

This study provides a useful comparison between three different intelligent controllers in terms of design, implementation and performance aspects for Permanent

Magnet Synchronous Motor (PMSM) drives. The intelligent controllers were found to be robust as compared to the conventional PI controller. The differences between these intelligent controllers are: design of conventional FLC is easier than ANN and NF controllers as it is based on simple linguistic control rules; FLC need a relatively high computation as compared to ANN and NF: (c) FLC suffer from the chattering phenomenon, which results in vibration of the motor; (d) Drive response for ANN controller is faster than FLC and NF: and (e) NF controller provides the smoothest speed response of the drive. From the above comparison, the hybrid neuro-fuzzy controllers appear to be the best ones since they provide the best performances and benefit from the respective advantages of ANN and FLC.

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