A Comparative Study of PI, IP and Neuro-Fuzzy Controllers for Induction Motor Drives

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Abstract--*This paper presents the comparative study of PI, IP-types and hybrid Neuro-Fuzzy control strategy for high-performance induction motor drives. Speed control performance of induction motors is affected by parameter variations and non linearities in the induction motor. Both the design of the PI, IP and ANFIS controller and its integration in the direct field control are discussed. The proposed control scheme is to improve the performance and robustness of the PI, IP and neuro-fuzzy controller induction motor drives under non linear loads and parameter variations. The neuro-fuzzy controller assures excellent qualities in terms of tracking, and disturbance rejection with high robustness comparative PI and IP controller. The effectiveness and feasibility of the structure developed is verified by several simulation tests with different conditions operating.*

Index Terms-- Induction motor drives, vector control, PI, IP, ANFIS controller.

1. NOMENCLATURE

s, r : Stator and rotor subscripts
d, q : Direct and quadrate Park subscripts
v, i, φ : Voltage/ Current/ Flux variables
R_S, R_R : Stator, rotor resistances
L_S, L_R : Stator, rotor inductance
L_m : Mutual magnetizing inductances
σ : Total leakage factor
ω_S : Stator frequency
ω_r : Slip frequency
ω_m : Nominal frequency
Ω : Rotor speed
θ_s : Rotor flux position
J : Inertia
f : Friction coefficient
T_e : Electromagnetic Torque
p : Pole pair number
^ : Superscript of estimated quantity
IM : Induction Motor

2. INTRODUCTION

High performance control techniques for induction motor drives are very fascinating and challenging subjects of research and development, and recently, they received wide attention in the literature. The Induction machine (IM) known by its robustness, cost, reliability and effectiveness is the subject of several researches. However, it is traditionally for a long time, used in industrial applications that do not require high performances, this because of its high non-linearity and its high-coupled structure. In the past years, many techniques for the control of IMs have been investigated. Among them, the field-oriented control is the most popular one.

With the technique of field orientation, the rotor speed is asymptotically decoupled from rotor flux, and the speed is linearly related to torque current [1], [2].

The most widely used controller in the industrial applications is the PI-IP-type controllers because of their simple structures and good performances in a wide range of operating conditions [3],[4]. In recent years, artificial neural network (ANN) and fuzzy logic controllers (FLC), have gained great important and witnessed a rapid growth in industrial applications. So,the researches were then directed toward another type of intelligent systems called "neuro-fuzzy systems" [5],[6],[7],[8] which prove their capabilities in solving most of the above limitations of neural networks [9] and ensuring by the way the robustness of the controlled process toward parameter variations, uncertainties of the and external perturbations. One of the most popular neuro-fuzzy systems are the adaptive neuro-fuzzy inference one (ANFIS) introduced by Jan et al. [10],[11],[12].

The motor drive is preliminary simulated and experimented with conventional digital PI, IP and ANFIS speed regulator in order to establish a term of comparison. The paper is structured as follows. Section 3 describes a mathematical of induction motor drive, Section 4 gives the structure of the direct field oriented control and the PI-IP-types control designs are discussed in this section. Section 5 gives the structure of Adaptive Neuro-Fuzzy Inference System control (ANFIS). Section 6 and 7 provide the simulation results and conclusions, respectively.

3. Dynamic model of induction motor

The dynamics of the induction motor in the *d-q* motor reference frame, which is rotating at the synchronously speed, can be simply described by the following nonlinear differential [1]:

where v_{sd}, v_{sq} , i_{sd} , i_{sq} , φ_{rd} and φ_{rq} are respectively, stator voltages, stator currents and rotor flux d-q components reference frame. ω_s and ω_r are the electrical synchronous stator and rotor speed; σ is the linkage coefficient, and T_s, T_r are the stator and rotor time constants:

$$\sigma = 1 - \frac{L_m^2}{L_s . L_r} \qquad T_r = \frac{L_r}{R_r} \qquad \text{and} \qquad T_s = \frac{L_s}{R_s}$$

The rotor speed is linked to the shaft motor speed by:

$$\omega_r = p.\Omega \tag{2}$$

Electrical rotor speed and the electromagnetic torque as given by:

$$\frac{d\omega_r}{dt} = \frac{3}{2} . \frac{p^2}{J} . \frac{L_m}{L_r} . \left(i_{sq} . \varphi_{rd} - . i_{sd} . \varphi_{rq} \right) - \frac{p}{J} . T_L - \frac{f}{J} . \omega_r \tag{3}$$

4. Rotor Field Oriented Control

This method is based on a nonlinear coordinate change, admitting a clear physical interpretation since corresponding to a rotation by the rotor flux angle. In these coordinates the equations of the induction motor are very similar to the equations of a DC motor. Since the control of DC motors is much simpler and better understood, field-oriented methods have become very popular [2].

$$\begin{bmatrix} \frac{d}{dt}i_{sd} \\ \frac{d}{dt}i_{sq} \\ \frac{d}{dt}\varphi_{rd} \\ \frac{d}{dt}\varphi_{rq} \end{bmatrix} = \begin{bmatrix} -\left(\frac{R_s}{\sigma.L_s}+\frac{1-\sigma}{\sigma.T_r}\right) & \omega_s & \frac{L_m}{\sigma.L_S.L_r.T_R} & \frac{L_m}{\sigma.L_S.L_r}.\omega_r \\ -\omega_s & -\left(\frac{R_s}{\sigma.L_s}+\frac{1-\sigma}{\sigma.T_r}\right) & \frac{L_m}{\sigma.L_S.L_r}.\omega_r & \frac{L_m}{\sigma.L_S.L_r.T_r} \\ \frac{L_m}{T_r} & 0 & -\frac{1}{T_r} & (\omega_s-\omega_r) \\ 0 & \frac{L_m}{T_r} & -(\omega_s-\omega_r) & -\frac{1}{T_r} \end{bmatrix} . \begin{bmatrix} i_{sd} \\ i_{sq} \\ \varphi_{rd} \\ \varphi_{rq} \end{bmatrix}$$

$$+\begin{bmatrix} \frac{1}{\sigma.L_S} & 0 \\ 0 & \frac{1}{\sigma.L_S} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} . \begin{bmatrix} v_{sd} \\ v_{sq} \end{bmatrix} \quad (1)$$

A. Direct Field Oriented Control

Its principle consists in exploiting the dynamic model of the motor by choosing a system of two-phase axis (d, q) to orient him according to the rotor flux, and canceling its quadratic component φ_{rq}. The d-axis is aligned with the rotor flux space vector. Under this condition we have: $\varphi_{rd} = \varphi_r$ and $\varphi_{rq} = 0$

In this case the torque and the synchronous angular speed equations become [3]:

$$T_e = p\frac{L_m}{L_r}\varphi_r i_{sq}$$

(4)

$$\omega_s = \omega + \frac{L_m i_{sq}}{T_r \varphi_r} \quad (5)$$

Using equations (1) we obtain the following voltage equations:

$$\begin{cases} v_{sd} = \sigma L_s \frac{di_{sd}}{dt} + R_s i_{sd} + \frac{L_m}{L_r}\frac{d\varphi_r}{dt} - \omega_s \sigma L_s i_{sq} \\ \quad = \sigma L_s \frac{di_{sd}}{dt} + R_s i_{sd} + e_{sd} \\ v_{sq} = \sigma L_s \frac{di_{sq}}{dt} + R_s i_{sq} + \omega_s \frac{L_m}{L_r}\varphi_r + \omega_s \sigma L_s i_{sd} \\ \quad = \sigma L_s \frac{di_{sq}}{dt} + R_s i_{sq} + e_{sq} \end{cases} \quad (6)$$

$$T_r \frac{d\varphi_r}{dt} + \phi_r = L_m i_{sq} \quad (7)$$

B. PI Speed Controller

The dynamic model of speed induction motor drive is significantly simplified, and can be reasonably represented by the bloc diagram shown in Fig.1.

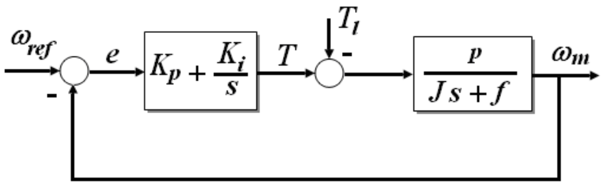


Fig. 1. Block diagram of speed PI-type controller

By using the Laplace transformation, the transfer function for (3) is equation (8):

$$\omega_m(s) = \frac{p(T-T_l)}{Js+f}$$

(8)

The classic numerical PI (Proportional and Integral) regulator is well suited to regulating the torque, to the desired values as it is able to reach constant reference, by correctly both the P term (K_p) and I term (K_i) winches are respectively responsible for error e sensibility and for the steady state error. If $T_l = 0$, the transfer function is as following (6):

$$G(s) = \frac{p(K_p s + K_i)}{Js^2 + (f + K_p p)s + K_i p}$$

(9)

where

$$P(s) = s^2 + \frac{f + K_p p}{J} s + \frac{K_i p}{J} = 0$$

(10)

The expressions for K_p and K_i of the regulator is calculated by Imposition of poles complexes combined with real part negative $s_{1,2} = \rho(-1 \pm j)$.

$$\begin{cases} K_p = \dfrac{2\rho J - f}{p} \\ K_i = \dfrac{2J\rho^2}{p} \end{cases} \quad (11)$$

where ρ is a positive constant.

B. IP Speed Controller

To improve the dynamic for transient state and avoid overshoots, the speed control is confided to an IP controller. The dynamic model of speed induction motor is significantly simplified, and can be reasonably represented by the block diagram shown in Figure 2. The transfer function of the rotor speed response to the drive input can be expressed by:

$$\frac{\Omega_r(s)}{\Omega_r^*(s)} = \frac{k_i \cdot k_T}{Js^2 + (f + k_p + k_T)s + k_i \cdot k_T}$$

(12)

where $k_T = p \cdot \dfrac{\varphi_r^2}{R_r}$

(13) $$\xi = \frac{f + k_p \cdot k_T}{2(J \cdot k_i \cdot k_T)^{1/2}}, \quad and \quad \omega_n = \frac{k_i \cdot k_T}{J}$$

The expressions for kp and ki of the IP controller are calculated by imposition of complex poles combined with real part negative: $s_{1,2} = \rho(-1 \pm j)$. Owing to absence of zeros, the overshoot of the step response is avoided by setting the damping ratio ξ=1.

Subsequently, the proportional and integral coefficients, kp and ki, can be expressed by:

$$k_i = \frac{J \cdot \omega_n^2}{k_T} \quad and \quad k_p = \frac{2J \cdot \omega_n - f}{k_T}$$

(14)

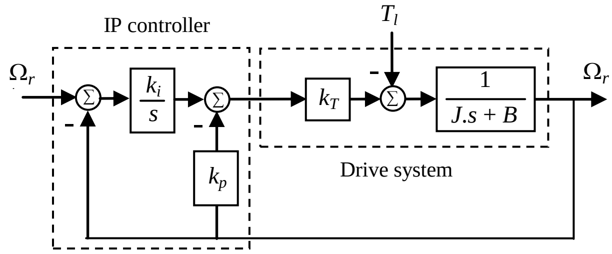


Fig. 2. Block diagram of speed IP-type controller

5. Adaptive Neuro-Fuzzy Inference System

The Adaptive Neuro-Fuzzy Inference System (ANFIS) has proven to be an excellent function approximation tool [10],[11]. ANFIS implements a first order Takagi-Sugeno fuzzy system. As a simple example, a fuzzy inference system with two inputs x_1 and x_2 and one output y is assumed. The first order Sugeno fuzzy model, a typical rule set with two fuzzy If–

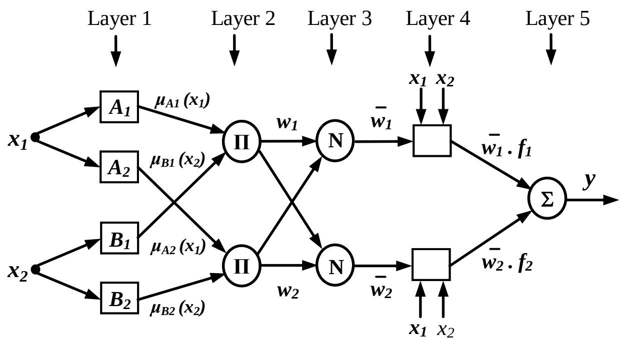


Fig 3. Neuro-Fuzzy Inference system configuration.

Then rules can be expressed as:

Rule 1: IF x_1 is A_1 AND x_2 is B_1 THEN y_1 =

$p_1 x_1+q_1 x_2+r_1$

Rule 2: IF x_1 is A_2 AND x_2 is B_2 THEN $y_2 = p_2 x_1+q_2 x_2+r_2$

The output y is the weighted average of the individual rules outputs and is itself a crisp value.

The corresponding ANFIS architecture is shown in Fig.3. Nodes at the same layer have similar functions. The output of the ith node in layer l is denoted as $O_{l,i}$. The information is propagated in five layers.

Layer 1: Every node i in this layer is an adaptive node with node function:

$O_{l,i} = \mu A_i(x)$ for i = 1,2, or

$O_{l,i} = \mu B_{i-2}(y)$ for i = 3,4.

where x (or y) is the input to the ith node and A_i (or B_{i2}) is a linguistic label (such as "low" or "high") associated with this node. In words, $O_{l,i}$ is the membership grade of a fuzzy set A (= A_1, A_2, B_1, or B_2) and it specifies the degree to which the given input x (or y) satisfies the quantifier A.

Layer 2: This layer consists of the nodes labeled Π which multiply incoming signals and send the product out. For instance,

$$O_{2,I} = w_i = \mu A_i(x)\ \mu B_i(y) \quad i = 1,2 \tag{15}$$

Each node output represents the firing strength of a rule.

Layer 3: In this layer, the nodes labeled N calculate the ratio of the ith rule's firing strength to the sum of all rules' firing strengths.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{16}$$

The outputs of this layer are called normalized firing strengths.

Layer 4: This layer's nodes are adaptive with node functions

$$O_{4,i} = \overline{w_i} y_i = \overline{w_i}\left(p_i x_1 + q_i x_2 + r_i\right) \tag{17}$$

where w_i is the output of layer 3, and $\{p_i,q_i,r_i\}$ are the parameter set. Parameters of this layer are referred to as consequent parameters.

Layer 5: This layer's single fixed node labeled Σ computes the final output as the summation of all incoming signals.

$$O_{5,i} = y = \sum_{i=1} \overline{w_i} y_i = \frac{\sum_i w_i y_i}{\sum_i w_i}$$

(18)

6. Results and Discussion

The structure of the proposed scheme in the fig 4 has been tested by simulation, in order to evaluate the performances of induction motor. The numerical values for the tested induction motor are summarized in table I. For all simulations performed in this paper, the best gain, found experimentally of PI controller are k_p = 0.6 and k_i = 15, and of IP controller are k_p = 2 and k_i = 20. Simulation results are given for motor sped tracking with the desired speed changing from the level to another (square-wave reference track with amplitude 150, 100 and 60 rad/s). Figs 5 and 6 show the speed trajectory when the desired speed changes from one value to another, using the PI controller, IP controller and ANFIS controller, respectively. The results were very successful, the ANFIS controller

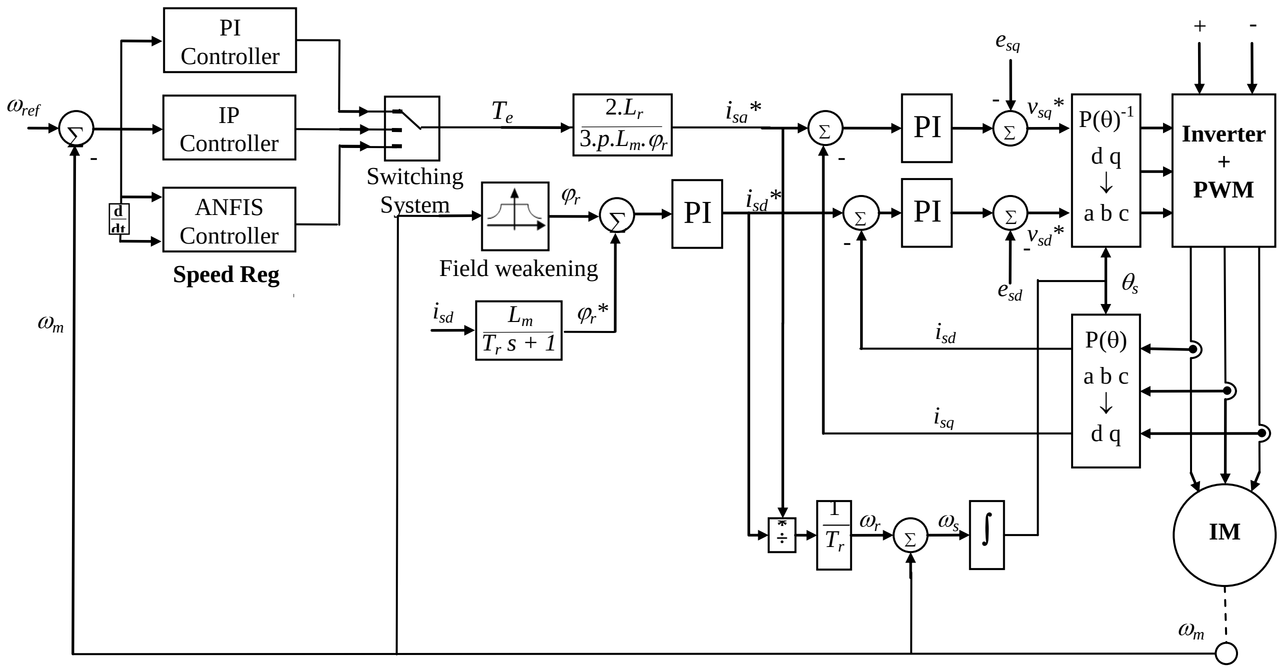


Fig 4. Block diagram of vector control for induction motor drive.

The network learning is realized with a hybrid algorithm [12] combining the techniques of least squares to estimate the consequent parameters, and back-propagation of the gradient to modify the premise parameters. To create a digital database for learning fuzzy-neural controller, we synthesized, and identified a fuzzy controller of Mamdani type, with five membership functions. The ANFIS controller has been defined, and submitted to off-line learning phase for identification. Figure 4 shows the block diagram of the direct filed oriented control of induction motor drive under PI, IP and ANFIS regulator.

reduces both the overshoot and extent of oscillations under the same operating conditions compared PI and IP controller. To demonstrate the robustness of the proposed controller, we assume that the parameters of stator resistance R_r and stator inductance L_s, have been perturbed from their nominal values in Figs 7 and 8. It is evident that the speed response of the ANFIS control is not affected by this variation.

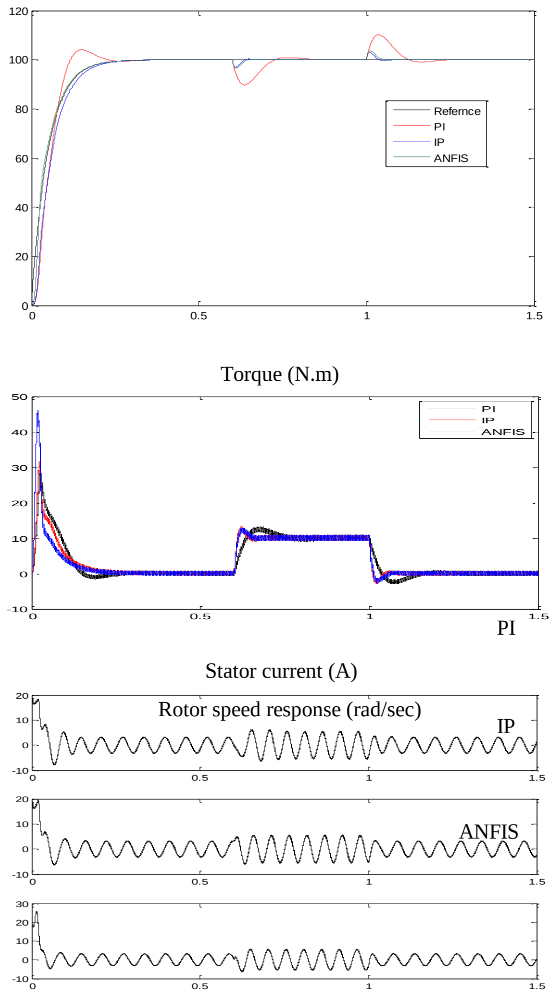
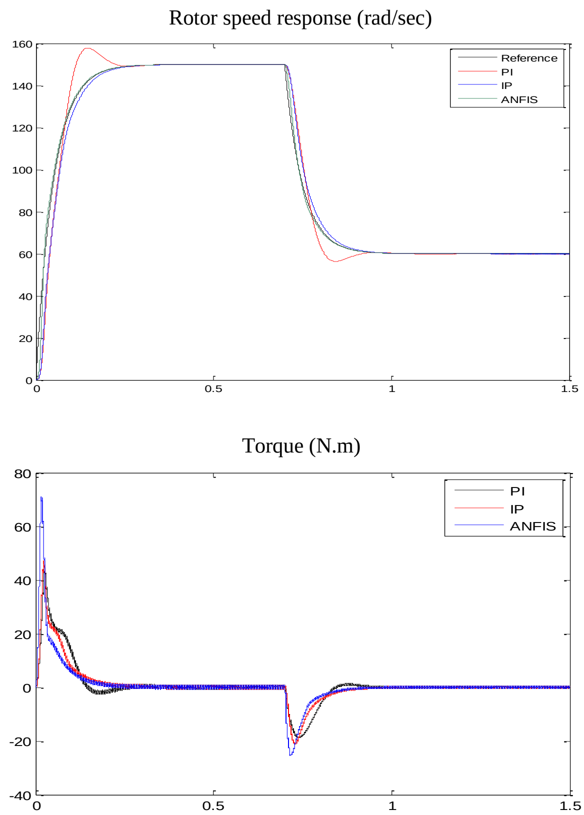


Fig. 5. Results of speed control system

To illustrate the effectiveness of the high-performance tracking control for induction motor, the proposed scheme controller was applied to control the motor under variable load torque.

It is observed from Fig.9, that the PI, IP and ANFIS controller closely tracks the motor speeds, even under changing conditions. Rejection of external disturbances is also achieved. Compared with the motor speed response with variable load, it can be seen that the undesirable oscillatory response is clearly evident. All test results show that the proposed ANFIS control strategy is very effective in tracking the selected tracks at all time, while the system transients are effectively reduced.



Stator current (A)

Rotor speed response (rad/sec)

Stator current (A)

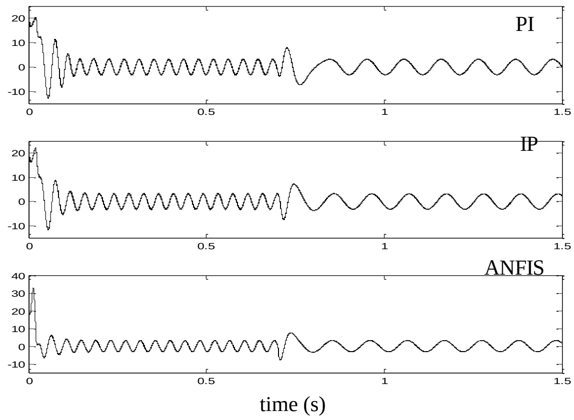


Fig. 6. Results of speed control system under reference variation

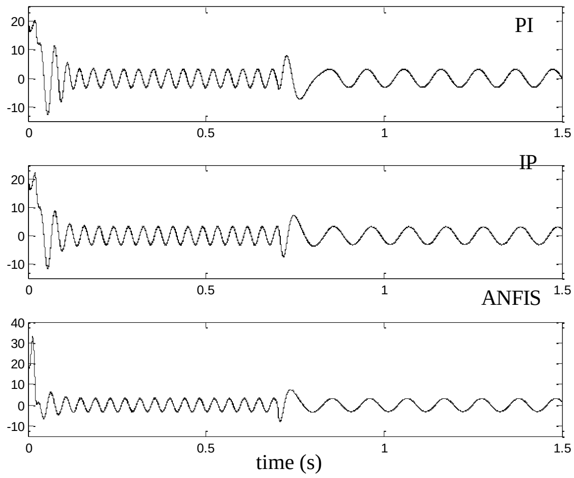
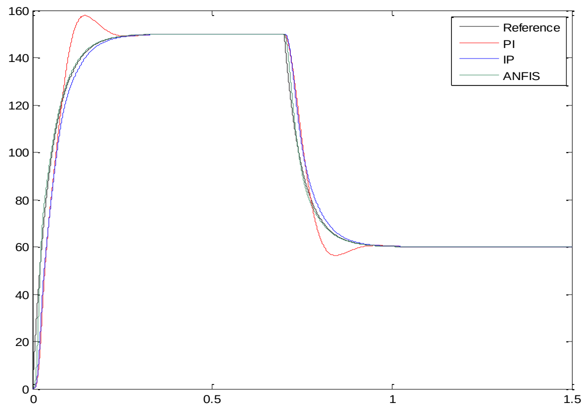
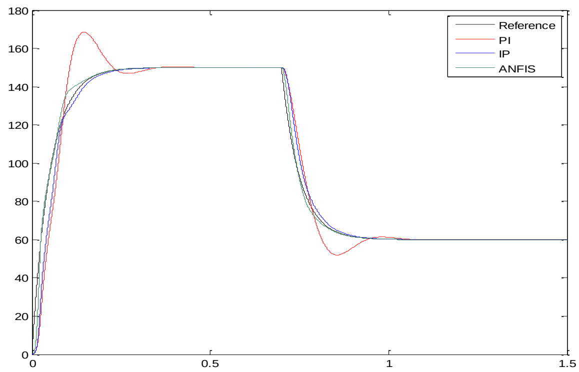
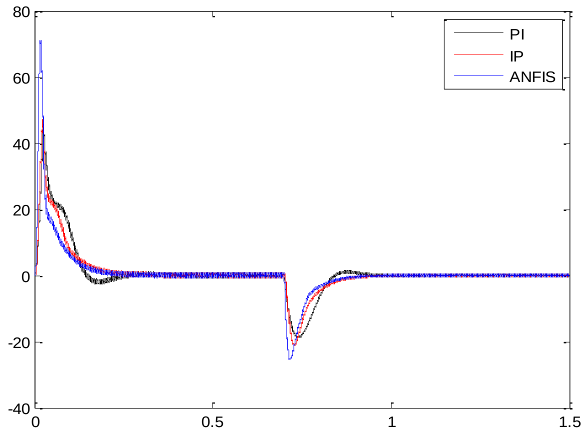


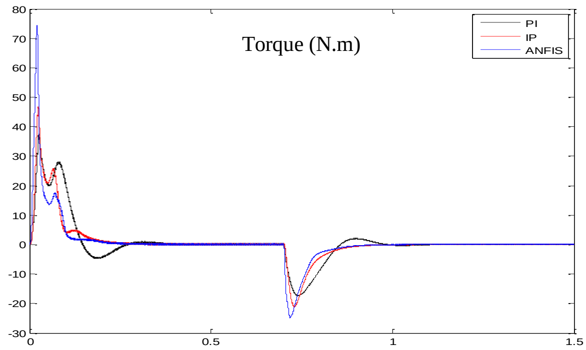
Fig 7. speed step response under stator resistance changes (Variation of +20 % Rs)





Torque (N.m)





time (s)

Stator current (A)

Stator current

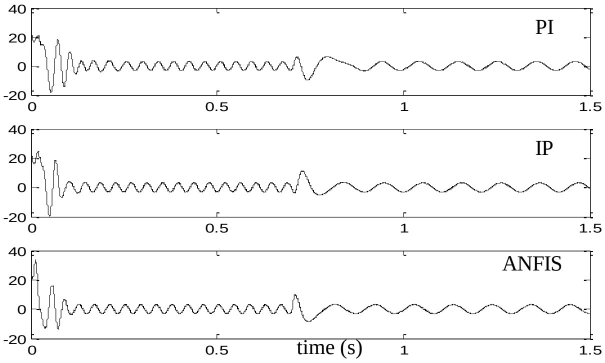
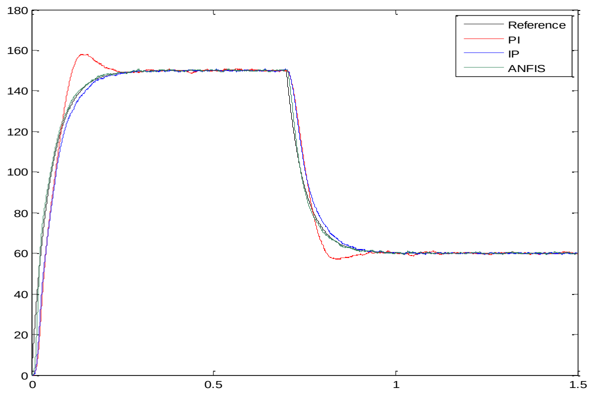


Fig.8. speed step response under stator inductance changes (Variation of +20 % Ls)

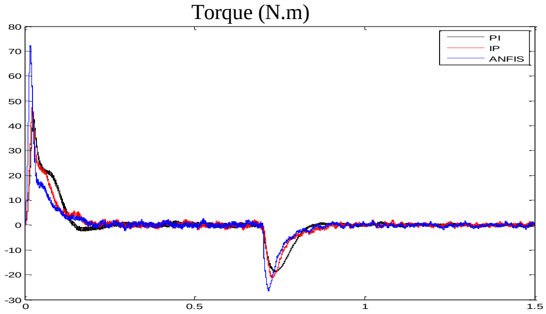
Rotor speed response (rad/sec)

time (s)

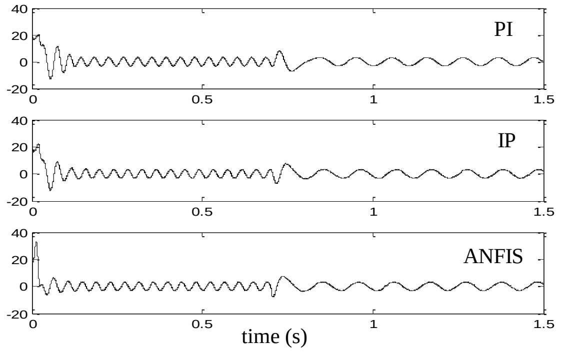
Rotor speed response (rad/sec)



Torque (N.m)



Stator current [A]



time (s)

Fig.9. Speed control using PI, IP and ANFIS under stochastic load torque changes

7. Concluding Remarks

In this paper a comparative study of PI, IP and hybrid fuzzy-neural network (ANFIS) for high-performance induction motor drives are presented. The proposed control system was analyzed and implemented in simulation. The successes of the controllers proposed are demonstrated by parameters variations under load conditions by applying a torque. The PI-type control presents an overrun important compared the IP and ANFIS controller. The IP and ANFIS controller have a good speed response, regardless of parameter variations or external load. The chief advantage of designing and implementing the proposed ANFIS controller is the ease of the design and flexibility.

Appendix

TABLE I: Rating of tested induction motor

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Rated values	*Power*	*1.5*	*kW*
	Frequency	50	Hz
	Voltage Δ/Y	220/380	V
	Current Δ/Y	11.25/6.5	A
	Motor Speed	1420	rpm
	pole pair (p)	2	
Rated parameters	Rs	4.85	Ω
	Rr	3.805	Ω
	Ls	0,274	H
	Lr	0,274	H
	Lm	0,258	H
Constant	J	0,031	kg,m²
	f	0.00114	Kg.m/s