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Comparative study between the conventional regulators and fuzzy logic controller: application on the induction machine

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Abstract. This paper proposes a new application approach for robust speed control induction machine using the equivalence modal principle. Indeed, the majority of the classic methods of regulation are ineffective in front of the variation of the parameters and uncertainties which can affect the model of the asynchronous machine. In order to get rid of this draw backs, an association of the fuzzy logic regulators with a strategy of vector control, applied to the asynchronous machines, is presented in this paper. Indeed, this law of control lends itself well to the regulation and the controlling of process with variable parameters during the time.
A comparative study of the indirect stator flux orientation control of induction motor drive by classic regulators (Integral Proportional (IP) and Proportional Integral (PI)) and fuzzy logic controller (FLC) is presented.
The robustness between these two regulators was tested and validated under simulations with the presence of variations of the parameters of the machine, in particular the rotor time-constant and face of disturbances of load torque.
In the objective of the real-time implementation of the regulator FLC, a neuro-fuzzy version is also presented.

Keywords. Induction machine, stator –flux-oriented control, Proportional Integral, fuzzy logic.

1 Introduction

AC motors, particularly the squirrel-cage induction motor (SCIM), enjoy several inherent advantages like simplicity, reliability, low cost and virtually maintenance-free electrical drives [1]. However, for high dynamic performance industrial applications, their control remains a challenging problem it is very complex due to the coupling of the physical parameters and they exhibit significant non-linearties.

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Several methods of control are used to control the induction motor among which the vector control or field orientation control that allows a decoupling between the torque and the flux, in order to obtain an independent control of torque and the flux like DC motors.

The overall performance of field-oriented-controlled induction motor drive systems is directly related to the performance of current control [2]. Therefore, decoupling the control scheme is required by compensation of the coupling effect between q-axis and d-axis current dynamics [3]–[4]-[5].

The simulation results studied in [2], [6] and [7] show that the conventional regulators do not make it possible to solve problems variations of the machine as well as the changes of load torque. Advanced strategies of control have drawn the attention of the control engineers in the last few years. A solution had been proposed on using a sophisticated method such as fuzzy logic controller (FLC) which lends itself very well to regulation and control to the understandable process using the appropriate conventional classic methods. Fuzzy logic control has excelled in dealing with systems that are complex, ill-defined, non-linear, or time-varying [8]. FLC is relatively easy to implement, as it usually needs no mathematical model of the controlled system. This is achieved by converting the linguistic control strategy of human experience or experts' knowledge into an automatic control strategy [9].

In this paper, we treat indirect stator flux orientation control (ISFOC) of induction machine with two types of regulators, conventional regulators (IP and PI) and the fuzzy logic controller (FLC).

Indeed [10] to develop and apply this technique to a system of regulation of level in a refinery tank [11]. Our idea had enlarged the study to controlling of an asynchronous machine, which made it possible to develop a technique of control in order to obtain satisfactory results in spite of the parametric variations or other types of disturbances. Which conform the originality of this work.

The paper is organized as follows. Section 2 presents the induction motor model employed.

Section3 describes the basic indirect stator field-oriented control (ISFOC) of induction motor. The synthesis of the conventional regulators is presented in Section 4. The fuzzy logic based proportional integral controller (FLPI) and using the modal equivalences is presented in Section 5. These controllers are evaluated and compared under simulations for a variety of operating conditions of the drive machine in Section5. Section 6 presents a comparative study between the two strategies of control. Finally, Section 7 presents a version of controller based in both fuzzy and neural networks techniques and a conclusion will be presented at the end of this paper.

2 Induction machine model

Using the dynamic model of an induction machine as a controlled plant may be expressed in terms of the d-q axes components in a synchronous rotating frame presented in [21], the voltage equations in terms of stator current and rotor flux linkage can be restated in matrix form as [12]:

$$\begin{bmatrix} \frac{d\phi_{ds}}{dt} \\ \frac{d\phi_{qs}}{dt} \\ \frac{di_{ds}}{dt} \\ \frac{di_{qs}}{dt} \\ \frac{d\omega_r}{dt} \end{bmatrix} = [A]\begin{bmatrix} \phi_{ds} \\ \phi_{qs} \\ i_{ds} \\ i_{qs} \\ \omega_r \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ \frac{1}{\sigma L_s} & 0 & 0 \\ 0 & \frac{1}{\sigma L_s} & 0 \\ 0 & 0 & -\frac{n_p}{J} \end{bmatrix}\begin{bmatrix} v_{ds} \\ v_{qs} \\ C_r \end{bmatrix} \quad (1)$$

Where:

$$[A] = \begin{bmatrix} 0 & \omega_s & -R_s & 0 & 0 \\ -\omega_s & 0 & 0 & -R_s & 0 \\ \frac{1}{\sigma T_r L_s} & \frac{\omega_r}{\sigma L_s} & -\frac{T_r + T_s}{\sigma T_r T_s} & \omega_{sl} & 0 \\ -\frac{\omega_r}{\sigma L_s} & \frac{1}{\sigma T_r L_s} & -\omega_{sl} & -\frac{T_r + T_s}{\sigma T_r T_s} & 0 \\ -\frac{n_p^2}{J} i_{qs} & \frac{n_p^2}{J} i_{ds} & 0 & 0 & -\frac{f}{J} \end{bmatrix}$$

$$\sigma = 1 - \frac{M^2}{L_s L_r}; T_s = \frac{L_s}{R_s}; T_r = \frac{L_r}{R_r}; \omega_{sl} = \omega_s - \omega_r$$

3 Indirect field-oriented control of induction motor

The main objective of the vector control of induction motors is, as in DC machines, to independently control the torque and the flux; this is done by using a d-q rotating reference frame synchronously with the stator flux space vector [13]. Then, the d-axis is aligned with the stator flux vector and the stator flux linkage to be constant, which means [12]:

$$\phi_{ds} = \phi_s ; \frac{d\phi_{qs}}{dt} = \phi_{qs} = 0 \quad (2)$$

Thus by taking into account these new conditions and employing (2) on the (1), the dynamic model of an induction machine became:

$$V_{ds} = \frac{R_s(T_s + T_r)}{T_r}(1 + \frac{\sigma T_r T_s}{T_s + T_r})i_{ds} - \sigma L_s\, \omega_{sl}\, i_{qs} - \frac{\phi_s}{T_r}$$
$$V_{qs} = \frac{R_s(T_s + T_r)}{T_r}(1 + \frac{\sigma T_r T_s}{T_s + T_r})i_{qs} + \sigma L_s\, \omega_{sl}\, i_{ds} + \omega \phi_s \qquad \textbf{(3)}$$

It can be seen that the voltage equations include two terms of coupling between d-axis and q-axis. These terms are considered as disturbances and are cancelled by using a decoupling method that utilizes nonlinear feedback of the coupling voltages [12].

Then, defined two new intermediate variables of decoupling whose expressions are as follows:

$$V_{ds1} = V_{ds} + E_d$$
$$V_{qs1} = V_{qs} + E_q \qquad \textbf{(4)}$$

With:

$$E_d = \sigma L_s \omega_{sl} i_{qs} + \frac{\phi_s}{T_r}$$
$$E_q = -\sigma L_s \omega_{sl} i_{ds} - \omega \phi_s \qquad \textbf{(5)}$$

After modeling the induction motor, we will be interested in the synthesis of the conventional regulators using of PI controller and IP controller.

4 Synthesis of the conventional regulators

4.1 Speed regulator type IP

The closed-loop speed transfer function is [21]:

$$\frac{\Omega(p)}{\Omega^*(p)} = \frac{1}{1 + \frac{1}{k_1 k_i} p + \frac{\tau}{k_1 k_i} p^2} \qquad \textbf{(6)}$$

With : $k_1 = k_p / (f + k_p)$

Where k_p and k_i denote proportional and integral gains of IP speed controller.

Since, the choice of the parameters of the regulator is selected according to the choice of the damping ratio (ξ) and natural frequency (ω_o):

$$\begin{cases} \dfrac{1}{k_1 k_i} = \dfrac{2\xi}{\omega_o} \\ \dfrac{\tau}{k_1 k_i} = \dfrac{1}{\omega_o^2} \end{cases} \tag{7}$$

4.2 Speed regulator PI

The closed-loop speed transfer function is [21]:

$$\frac{\Omega(p)}{\Omega^*(p)} = \frac{\left(k_p p + k_i\right)}{Jp^2 + \left(f + n_p k_p\right) p + n_p k_i} \tag{8}$$

It can be seen that the motor speed is represented by second order differential equation:

$$p^2 + 2\xi\omega_o\, p + \omega_o^2 = 0 \tag{9}$$

By identification, we obtain the following parameter:

$$\begin{cases} k_p = 2\xi\omega_o J - f \\ k_i = J\omega_o^2 \end{cases} \tag{10}$$

4.3 Currents regulator with PI controller

The transfer functions of the stator currents are obtained from the system equation (3) and by canceling E_d and Eq by the feed forward compensation term [12]:

$$\begin{aligned} V_{ds1} &= V_{ds} + E_d = \frac{R_s\left(T_s + T_r\right)}{T_r}\left(1 + \frac{\sigma T_s T_r}{T_s + T_r} p\right) i_{ds} \\ V_{qs1} &= V_{qs} + E_q = \frac{R_s\left(T_s + T_r\right)}{T_r}\left(1 + \frac{\sigma T_s T_r}{T_s + T_r} p\right) i_{qs} \end{aligned} \tag{11}$$

From (11), we obtain:

$$G_d(p) = G_q(p) = \frac{k_c}{1+\tau_c p} \tag{12}$$

Where $k_c = \dfrac{T_r}{R_s\left(T_s + T_r\right)}$ are is a gain and $\tau_c = \dfrac{\sigma T_s T_r}{T_s + T_r}$ is a time constant.

Then the closed-loop current transfer function is:

$$H_i^{BF}(p) = \frac{\omega_n^2}{p^2 + 2\xi\omega_n p + \omega_n^2}\left(\frac{k_{ip}}{k_{ii}} p + 1\right) \tag{13}$$

This allows us to write finally:

$$\begin{cases} k_{ip} = \dfrac{2\xi\omega_n\tau_c - 1}{k_c} \\ k_{ii} = \dfrac{\omega_n^2\tau_c}{k_c} \end{cases} \tag{14}$$

5 Fuzzy logic controller

Historically, the first fuzzy logic regulator which appeared is that Mamdani. Then, other types of fuzzy controllers were defined; in particular that of Sugeno in 1985 [14].

When an expert understands qualitatively the process dynamics, it is possible to specify a qualitative control strategy using linguistic rules, named fuzzy rules. A classical example of those fuzzy control configurations is shown in fig. 1[15].

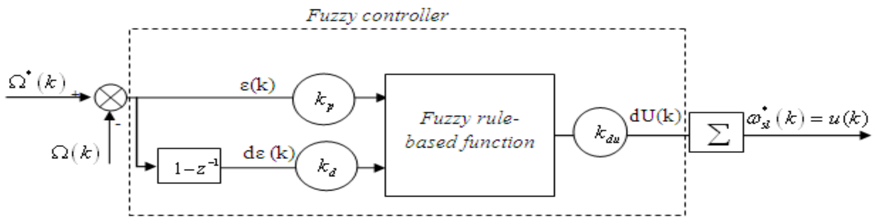

Fig. 1. *Synoptic diagram of a speed fuzzy controller*

We find in the input and in the output of the fuzzy controller gains named "factors of scale" which allow changing the sensitivity of the fuzzy regulator without changing its structure [16].

In the continuation, we are interested in another form of fuzzy regulator using the concepts of the principles modal equivalences. This regulator takes as a starting point the parameters of the regulator proportional integral (PI).

5.1 Synthesis of a fuzzy regulator by application of the principle of modal equivalences

The PI transfer function connecting the error ε to the control signal u expressed in z is:

$$\frac{u(z)}{\varepsilon(z)} = k_p + k_I\left(\frac{z}{z-1}\right) \tag{15}$$

Where k_p and k_I, are the gains of the PI controller.
From (15), we obtain the following equation:

$$u(z)\left(1-z^{-1}\right) = k_p(1-z^{-1})\ \varepsilon(z) + k_I\ \varepsilon(z) \tag{16}$$

If we note respectively $\delta\varepsilon$ the change of the error ε and δu the change of the signal control u then (16) becomes:

$$\delta u = k_p\ \delta\varepsilon + k_I\ \varepsilon \tag{17}$$

From fig. 4, it is noticed, that the output of regulator PI controller is according to the error ε and of its change $\delta\varepsilon$. Then, it appears completely natural to preserve the same inputs and output for the fuzzy controller equivalent.

5.2 Universes of discourse partition

To avoid at most introducing nonlinearities into the fuzzy controller, a regular triangular partitioning is carried out on each universe of discourse [10].
The Fig. 2 illustrates the partition of the fuzzy subsets on the universe of discourse associated to the error. To simplify the calculation, the distribution of the membership functions will be supposed symmetric with regard to zero. What returns us to take $\varepsilon_0 = \delta\varepsilon_0 = \delta u_0 = 0$.

The distribution of the various membership functions is obtained according to the following formula:

$$\varepsilon_i = i\,\Delta a + \varepsilon_0 \tag{18}$$

Where: Δa is the difference between two consecutive membership functions.

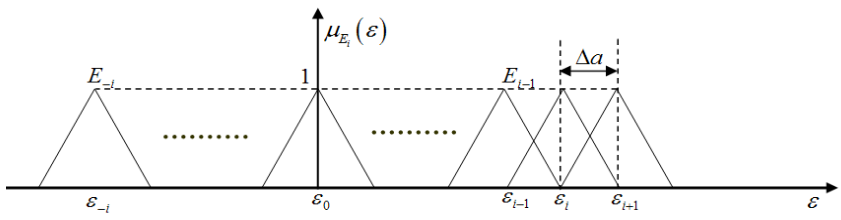

Fig. 2. *Fuzzy partition of the universe of discourse associated to the error*

In the same way for the change of the error $\delta\varepsilon$ and the change of the control signal δu , we obtain:

$$\begin{aligned} \delta\varepsilon_j &= j\,\Delta b + \delta\varepsilon_0 \\ \delta u_k &= k\,\Delta c + \delta u_0 \end{aligned} \tag{19}$$

With Δb is the difference between two consecutive membership functions relating to the change of the error and Δc is the difference between two consecutive membership functions relating to the change of control signal.

5.3 The fuzzy rule base model

Once the inputs and output of the fuzzy controller for whom we try to synthesize and their operating range on any universe of discourse were defined. It remains now to determine the rules base which is, in the case of a controller of type Mamdani, can be written:

$$\textbf{If } \varepsilon \text{ is } E_i \textbf{ and } \delta\varepsilon \text{ is } dE_j \textbf{ then } \delta u \text{ est } dU_{f(i,j)} \tag{20}$$

The application of the principle of modal equivalences leads to the following constraint:

$$\delta u_{f(i,j)} = k_p\,\delta\varepsilon_j + k_I\,\varepsilon_i \tag{21}$$

Substitution of (18) and (19) in (21), gives

$$f(i,j) = j\,k_p\left(\frac{\Delta b}{\Delta c}\right) + i\,k_I\left(\frac{\Delta a}{\Delta c}\right) \tag{22}$$

If we put: $\alpha = k_I \left(\frac{\Delta a}{\Delta c} \right)$ and $\beta = k_p \left(\frac{\Delta b}{\Delta c} \right)$, we obtain :

$$f(i, j) = i\ \alpha + j\ \beta \tag{23}$$

With: α and β being integers verifying $BCD(\alpha, \beta) = 1$.

Finally, the distribution of the membership functions is carried out in order to check the following relation:

$$\frac{\Delta c}{\Delta a} = \frac{k_I}{\alpha} \quad \text{and} \quad \frac{\Delta c}{\Delta b} = \frac{k_p}{\beta} \tag{24}$$

The ratio $\frac{\alpha}{\beta}$ is a proportionality factor between the ratio $\frac{k_p}{k_I}$ and $\frac{\Delta a}{\Delta b}$.

In that, it thus joins in a method directed synthesis and so differs from existing works, directed analyze.

The practical implementation of the synthesized fuzzy controller now requires to give an actual value to each parameter $\Delta a, \Delta b, \Delta c, \alpha$ and β. If no constraint is imposed on the distribution of the membership functions, in other term if the finale number of rules is not limited, a simple choice consists in fixing $\alpha = \beta = 1$. We obtain then the rules base summarized in the table. 1 [10].

Error ε

Change of error δε

dU	......	E_{-2}	E_{-1}	E_0	E_1	E_2	......
......	......	......	......	......	......	......	......
dE_2	......	dU_0	dU_1	dU_2	dU_3	dU_4	......
dE_1	......	dU_{-1}	dU_0	dU_1	dU_2	dU_3	......
dE_0	......	dU_{-2}	dU_{-1}	dU_0	dU_1	dU_2	......
dE_{-1}	......	dU_{-3}	dU_{-2}	dU_{-1}	dU_0	dU_1	......
dE_{-2}	......	dU_{-4}	dU_{-3}	dU_{-2}	dU_{-1}	dU_0	......
......	......	......	......	......	......	......	......

Table. 1. *The control rules for FLC*

We can notice that we have arrived at the table of inference that we will be able to obtain it by applying the method of Mac Vicar-Whelan [18].

For the adjustment of the fuzzy controller, we can play on one of these parameters $\Delta a, \Delta b$ and Δc or the coefficients α and β so that the equality (24) is satisfied.

Since the values of the regulator proportional integral regulator (K_p and K_I) are supposed to be known, it now remains to determine Δa, Δb, Δc, α and β.

For: $\begin{cases} k_p = 0.3 \\ k_I = 0.03 \end{cases}$ and $\begin{cases} \alpha = 1 \\ \beta = 10 \end{cases}$, we find these various values of Δa, Δb and Δc:

$$\begin{cases} \Delta a = \Delta b = 3 \\ \quad et \\ \Delta c = 0.03 \end{cases} \quad (1) \qquad \begin{cases} \Delta a = \Delta b = 0.5 \\ \quad et \\ \Delta c = 0.03 \end{cases} \quad (2)$$

$$\begin{cases} \Delta a = \Delta b = 0.25 \\ \quad et \\ \Delta c = 0.03 \end{cases} \quad (3) \qquad \begin{cases} \Delta a = \Delta b = 0.5 \\ \quad et \\ \Delta c = 0.03 \end{cases} \quad (4)$$

The simulation results obtained with these various values are given in fig. 3.

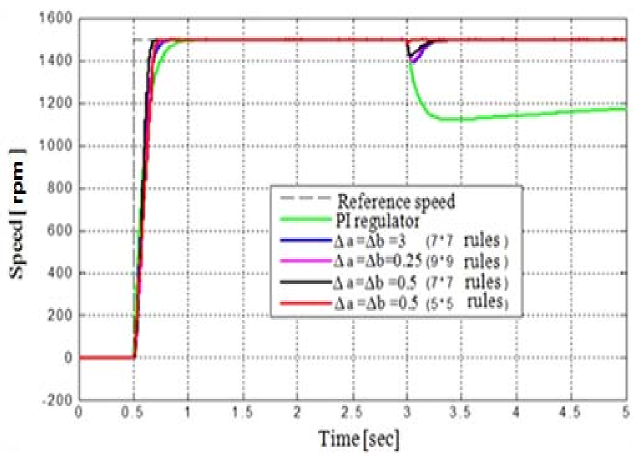

Fig. 3. *Simulation results obtained for the various values of Δa, Δb and Δc*

It is noted that the use of 5 or 7 symbol for ε and $\delta\varepsilon$ allows obtaining a relatively satisfactory response. We also note that, when we vary the number of rule or the distance between the various symbols, the machine response also varies (response time and the rejection of the disturbance of the load). It thus is impossible to obtain a Mamdani controller of size restricted by simply exploiting the basic adjustments on $\Delta a, \Delta b$ and Δc .

The other disadvantage is the significant number of rule used for the regulation, but the interest of the FLC is that only a small number of rules are necessary.

In spite of that, the synthesized fuzzy regulator imported improvement on the dynamics of the system especially point of view it is not so sensitive to the variation of load torque contrary to target PI regulator (see fig. 3).

6 Implementation and results

Simulations were performed using the conventional controllers (PI and IP) and the fuzzy logic controllers (FLPI and FL using the principle of modal equivalences (FLME)). These controllers are evaluated and compared under simulations using the Matlab-Simulink software.

Next, the robustness of each controller against system parameters variations are evaluated by the settling time, overshoot and rejection of load disturbances. These values are calculated by application of load disturbances at 5.5 sec, while the system parameters are varied from -80% to +80% of the nominal values. First for a variation from -80% to 80% of rotor resistance Rr, second for a variation from -80% to 80% and of moment of inertia J. The comparison results are indicated in Figs. 4 and 5.

Next, these controllers are evaluated and compared under simulations for a variety of operating conditions of the drive machine.

In this study, we evaluate these three criteria:

- Settling time: it corresponds to time puts by the speed to reach 999, 98 rpm for reference speed from -1000 to 1000 rpm.
- Overshooting: it corresponds to the difference between the reference speed and real maximum speed to reach at the time of this level.
- Time of rejection of the disturbance: it corresponds to time that puts the speed to return in the reach [999,98 , 1000,02] rpm at the time of application of load torque of 10Nm with reference speed of 1000 rpm.

According to the simulation results, the variation of the rotor resistance R_r has a big influence on the settling time of the system using a PI and IP regulator, whether it is at the settling time, the time of rejection of disturbance and overshooting.

In fig 4. (a), the FLPI is faster compared to the fuzzy FLME what especially causes a overshooting during a big variation of Rr (figure 4. (c)).

From fig 4. (b), we notice that the FLME has the best time of rejection of disturbance with regard to the other regulators.

According to figure 5. (b), we observe a better settling time of PI regulator compared to the other regulators. But this improvement is accompanied by a great overshooting towards the reference speed during a great variation of J (figure 5. (c)).

According to the results simulations results, the fuzzy regulator obtained by the application of the principle of modal equivalences (FLME), with license to obtain the best performances wished for implementation in the loop of speed regulation.

The fuzzy logic regulators (FLPI and FLME) are less sensitive to the moment inertia variation; since it reaches speed command with a overshooting much lower compared to PI and IP regulators (fig 5. (c)).

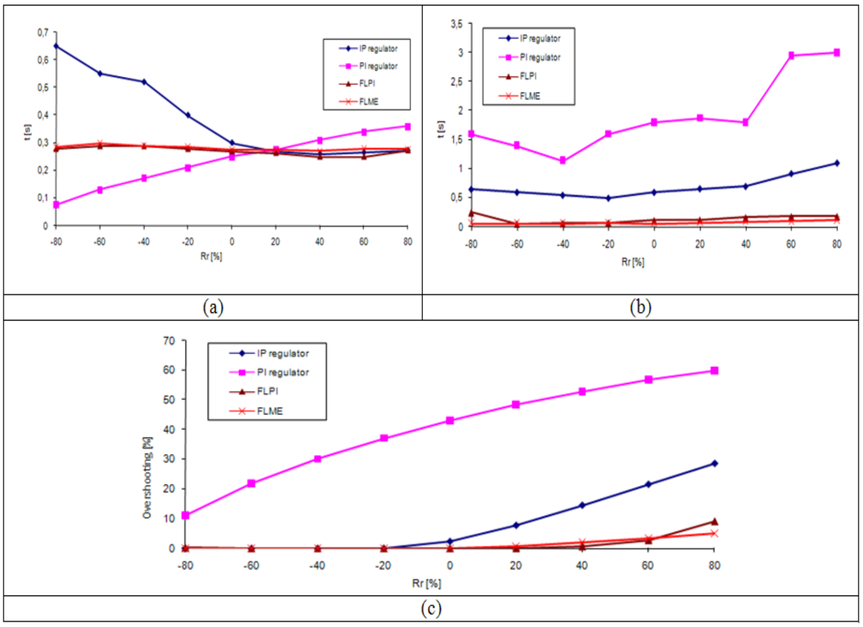

Fig. 4. *Reaction of the various speed regulators for a variation from -80% to +80 of* R_r

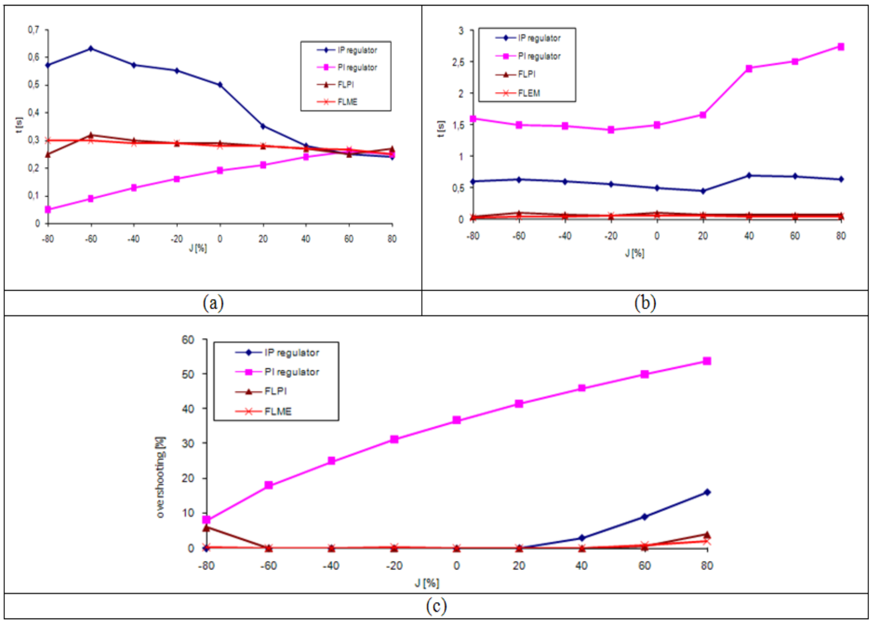

Fig. 5. *Reaction of the various speed regulators for a variation from -80% to +80 of J*

We as notice, as the fuzzy logic regulator obtained using the principle of modal equivalence, keep the same performances (settling time, time of rejection of disturbance and overshoot) for big variations of J.

7 Neuro-fuzzy regulator

In our case, the fuzzy regulator obtained by the principle of modal equivalence has a very important base of rules what makes its real time implementation heavy and difficult.

It is suitable to use instead a more sophisticated controller based on both fuzzy and neural networks techniques. In fact, this neuro-fuzzy controller is based on the training of a specified feedforward neural network which will replace overall steps of the Mamdani fuzzy standard controller [19].
The figure 7 shows the training bloc diagram steps of both controllers.

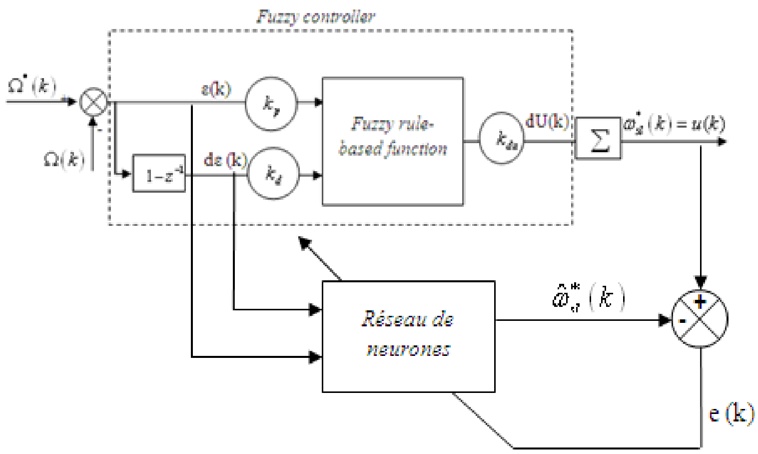

Fig. 6. *Neural-network learning.*

7.1 Neural networks model structure

We shall train a feedforward neural network of three layers (1 input layer, 1 hidden layer and 1 output layer). The input layer has 6 input neurons as shown in figure 7. While the output layer exhibits the corresponding fuzzy controller output. The hidden layer has 9 hidden neurons.

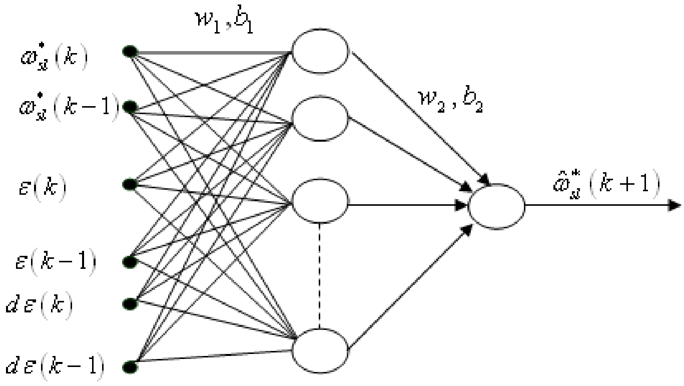

Fig. 7. *Neural-network structure*

We define the prediction error $e(k)$ as:

$$e(k) = \omega^*_{sl}(k) - \hat{\omega}^*_{sl}(k) \qquad \textbf{(25)}$$

The neural network is then trained to represent the non-linear function $f[.]$:

$$\omega^*_{sl}(k+1) = f\left[\omega^*_{sl}(k)\ \omega^*_{sl}(k-1)\ \varepsilon(k)\ \varepsilon(k-1)\ d\varepsilon(k)\ d\varepsilon(k-1)\right] \qquad \textbf{(26)}$$

The training procedure consists in sequentially adjusting the network weight vectors, so that the mean squared error between the desired response (the values from the target vector) and the network output is minimized [19],[20]:

$$J(k) = \sum_{i=1}^{k}\left[\omega^*_{sl}(k) - \hat{\omega}^*_{sl}(k)\right]^2 \qquad \textbf{(27)}$$

The activation functions are hyperbolic tangent sigmoid transfer function $\psi(x)$ for the first layer and linear for the second layer, let:

$$\psi(x) = \frac{2}{(1 + \exp(-2 * x)) - 1} \qquad \textbf{(28)}$$

The neural-model for the fuzzy logic controller can be expressed as:

$$\omega^*_{sl}(k+1) = w_2\left[\psi(w_1\varphi(k) + b_1)\right] + b_2 \qquad \textbf{(29)}$$

With: $\varphi^T(k) = \left[\omega^*_{sl}(k)\ \omega^*_{sl}(k-1)\ \varepsilon(k)\ \varepsilon(k-1)\ d\varepsilon(k)\ d\varepsilon(k-1)\right]$

Where w_1, w_2, b_1 and b_2 are the weights and biases matrices of the neural network.

The neural network with the constant values for the weight vectors, obtained after the training, represents the non-linear model of the FLC. Thus when a certain stop criteria is satisfied the training algorithm gives a set of optimal values of the weight vectors. The corresponding neural network training error is shown on the figure 8.

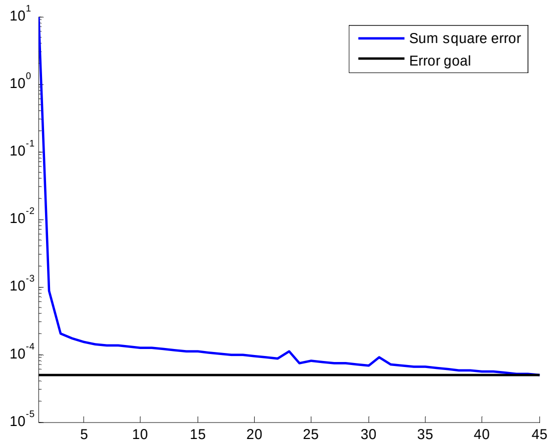

Fig. 8. *Neural-network training*

7.2 Simulation results

After the training phase, we have replaced the fuzzy controller by the neural network based one in order to test its generalization behaviour. With this new controller we find out that its performances are acceptable in both tracking and regulation settings and it is also robust in presence of parametric variations. The related simulation results are given in Figure 9.

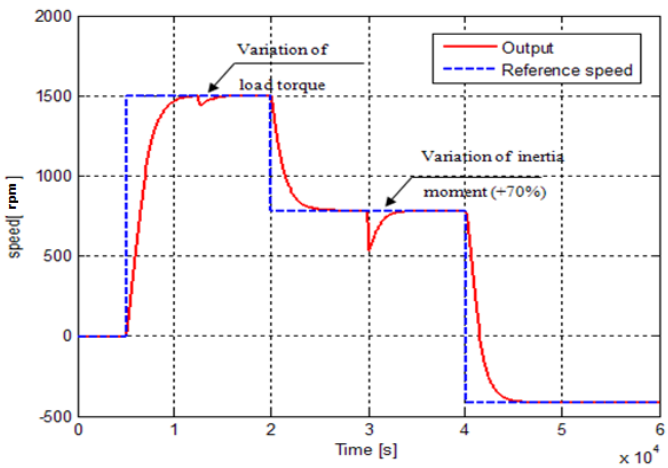

Fig. 9. *Response of the neural network regulator*

8 Conclusion

In this paper, a stator field orientation of induction motor has been presented.

The simulation results have enabled to us to judge the robustness of fuzzy controller comparing with the classical control.

We notice that the obtained results by using regulators with fuzzy logic of point of view insensitivity towards the variations of the external and internal disturbances (that is parametric variations) are very satisfactory. Which confirmed our approach.

It is to indicate also the good behavior of the neuro-fuzzy regulator during the existence of the parametric variations.

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Appendix

$v_{ds}, {}_{qs}$	: *d*, *q*-axis stator voltage components.
i_{ds}, i_{qs}	: *d*, *q*-axis stator current components.
$\Phi_{ds}, {}_{qs}$	: *d*, *q*-axis stator flux components.
R_s, R_r	: Stator and rotor winding resistance.
L_s, L_r	: Stator and rotor self-inductance.
M	: Mutual inductance.
n_p	: Number of pole pairs.
p	: Differential operator.
ω_s, ω_r	: Synchronous and rotor angular speed.
C_e, C_r	: Electromagnetic and load torque.
J	: Moment of inertia.
f	: Friction constant.
σ	: Total leakage constant
BCD	: The Biggest Common Divisor
ω_{sl}	: Slip angular speed