Artificial Intelligence Techniques for Induction Motor Drives

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***Abstract*— The induction machine has proved to be an appropriate solution for most industrial applications; Moreover, it presents the future of sustainable automotive industry due to the strategies of control and command of which it can be equipped. This paper presents a study of advanced methods applied to the control of induction machine in order to obtain a system satisfying the criterion of robustness. This work has been done as a comparison between the conventional controller and the advanced techniques of control such as fuzzy logic and artificial neural network. The results of various simulation tests highlight the robustness properties of the different control strategies based on orientation of the rotor flux.**

Keywords— Induction machine, advanced methods, conventional controller, criterion of robustness, fuzzy logic, artificial neural network.

I. INTRODUCTION

Nowadays, the induction machine dethrones the DC machine in the field of speed variation due to some of their advantages such as mechanical robustness, simple construction, and less maintenance [1]. It turns out a proper solution for most industrial applications; furthermore, the vector control strategies provide it behaviors and performances equivalent to those of a DC machine by performing a decoupling between the flux and the electromagnetic torque [6][7]. Among the techniques of control used in induction machine command we can find those based on the knowledge of the machine's parameters and the environment in which it is intended, therefore we speak about classic controllers (PI, PID ...). However, many challenges remain, the influence of internal parameters, the sensitivity to external disturbances, the presence of a mechanical sensor, and many other problems have given rise to new approaches in the field of induction machines command. It is therefore the application of fuzzy logic and neural networks [6][10].

The Artificial Intelligence techniques, such as, Fuzzy Logic and Artificial Neural Network have recently been applied widely in motor drives. The base element in fuzzy controller is fuzzy logic, it can be designed to approximate any nonlinear function without an explicit model of the plant, however this controller is regarded more tentative than an accurate faithful reflection [7]. An artificial neural network is composed of large interconnected processing elements (neurons) working in parallel to solve a specific task, by learning process it can be applied for pattern recognition or data classification [7] . A neural controller had the capabilities to imitate the behavior of nonlinear complex systems and the robustness face to disturbances, and in order to control a process it begin first by an identification step and a step of control [6].

The objective of this work is to know the contribution of these techniques of control on the induction machine drives. This paper is structured as follows: the first section shows the vector control of the asynchronous machine by orientation of the rotor flux. In the second and the third section, the machine is controlled respectively by a fuzzy controller, and a neural controller. Finally, the paper finished with a phase of tests and simulations to validate the performance and robustness of the techniques used, at the end a comparative synthesis of different strategies of control presented.

II. INDIRECT VECTOR CONTROL BY ORIENTATION OF ROTOR FLUX

The principle of which is based the vector control by orientation of rotor flux is to remove the internal coupling of the machine and return it to a linear control similar to that of a continuous current machine with a separated excitation [2][6].

For the realization of the vector control, there are two methods: the direct method and the indirect method. This study is based on the indirect one ; it uses the position of the rotor flux and it requires the use of a speed sensor.

The equations of tensions, fluxes rotor and the electromagnetic torque in a frame of reference (d, q) turning at a speed ω_s in comparison with the stator are:

$$\begin{cases} V_{rd} = R_r . I_{rd} + \frac{d\Phi_{rd}}{dt} - \omega_r . \Phi_{rq} \\ V_{rq} = R_r . I_{rq} + \frac{d\Phi_{rq}}{dt} + \omega_r . \Phi_{rd} \end{cases} \quad (1)$$

$$\begin{cases} \phi_{rd} = L_r . I_{rd} + M . I_{sd} \\ \phi_{rq} = L_r . I_{rq} + M . I_{sq} \end{cases} \quad (2)$$

$$C_{em} = \frac{P.M}{L_r} (\Phi_{rd} . I_{sq} - \Phi_{rq} . I_{sd}) \quad (3)$$

Where

(V_{rd}, V_{rq}): rotor voltage

(ϕ_{rd}, ϕ_{rq}): Rotor flux

(I_{rd}, I_{rq}): Current rotor

(I_{sd}, I_{sq}): Current stator

ω_r: Rotor pulsation

ω_s: Stator pulsation

R_r, L_r: Rotor and inductance resistance

P: pole pairs

M: Mutuale inductance

The axis mark (d, q) is oriented along the axis carrying the vector of the rotor flux so we have

$$\phi_{rq} = 0 \,;\, \phi_{rd} = \phi \tag{4}$$

With the condition (4), the expressions of torque and flux simplifies to:

$$C_{em} = \frac{P.M}{L_r}.\phi.I_{sq} \tag{5}$$

$$\phi = \frac{M}{1+T_r.s}.I_{sd} \tag{6}$$

Where

T_r: Rotor time constant

The decoupling by compensation is intended to decouple the axes d and q. This decoupling makes it possible to write the equations of the machine and of the regulation part in a simple manner and thus easily calculate the coefficients of the regulators. The expression of the stator voltages in the Laplace form are given as:

$$\begin{cases} V_{sd} = (R_s + \sigma.L_s.s)I_{sd} - \omega_s.(\sigma.L_s.I_{sq}) \\ V_{sq} = (R_s + \sigma.L_s.s)I_{sq} + \omega_s.(\sigma.L_s.I_{sd}) + \omega_s.\frac{M.\phi}{L_r} \end{cases} \tag{7}$$

And it can be simplifies to :

$$\begin{cases} V_{sd} = V_{sd\_r} + V_{sd\_c} \\ V_{sq} = V_{sq\_r} + V_{sq\_c} \end{cases} \tag{8}$$

With:

$$\begin{cases} \mathrm{V_{sd\_r}} = (\mathrm{R_s} + \sigma.\mathrm{L_s}.\mathrm{s})\mathrm{I_{sd}} \\ \mathrm{V_{sq\_r}} = (\mathrm{R_s} + \sigma.\mathrm{L_s}.\mathrm{s})\mathrm{I_{sq}} \end{cases} \tag{9}$$

$$\begin{cases} V_{sd\_c} = -\omega_s.(\sigma.L_s.I_{sq}) \\ V_{sq\_c} = +\omega_s.(\sigma.L_s.I_{sd}) + \omega_s.\frac{M.\phi}{L_r} \end{cases} \tag{10}$$

Where

L_S: Inductance stator

S: Laplace operator

$\sigma = 1 - \frac{M^2}{L_r.L_s}$ Represents the dispersion coefficient

The system studied in this work is composed of three PI controllers, which one is for speed regulation and the two others for currents regulation(I_{sd}, I_{sq}). The Figure (1) shows the loop control of current stator during the d_axis and the speed control loop is shown on the figure (2).

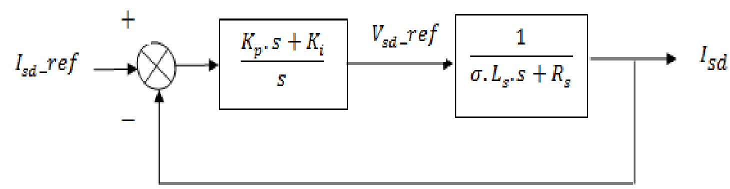

Fig. 1. Current stator loop control

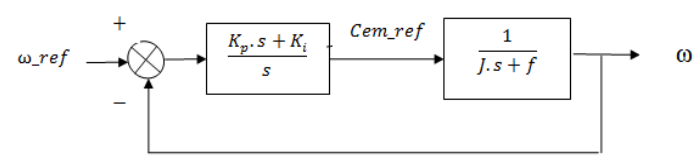

Fig. 2. Speed loop control

With K_P and K_i represent respectively the proportional and the integral gain. The parameters were calculated by the method of poles compensation (See Appendix).

III. VECTOR CONTROL BASED ON A FUZZY CONTROLLER

The basic principle of a fuzzy controller approaches the human approach in the sense that the treated variables are not logical in the sense of binary logic (for example) but linguistic variables. Moreover these linguistic variables are processed using rules that refer to certain knowledge of the system behavior.

The design of a fuzzy logic controller starts by assigning the input and output variables. The speed error reference value and its time variation has been selected as the inputs and the electromagnetique torque as the output [6]

A. Fuzzification and data base preparation:

The step of fuzzification is concerned with the processing of digital values to a fuzzy input values using the databases [6].

The fuzzification must be made a priori The universe of discourse of all the input and output variables are established as (- 1, +1). The suitable scaling factors are chosen to brought the input and output variables to this universe of discourse.

In this study each universe of discourse is divided into five overlapping fuzzy sets: NL (Negative Large), NS (Negative Small), ZE (Zero), PS (Positive Small) and PL (Positive Large). For the choice of the membership functions form, the triangular one has been chosen for all the membership functions with the exception of the extremities of each function whose trapezoidal form is used .The table 1 shows the distribution of the fuzzy sets for speed regulation.

TABLE I. DISTRIBUTION OF FUZZY SETS FOR THE SPEED REGULATION

Signification	Symbol	Speed error	Speed error time variation	Electromagnetic torque time variation
Negative Large	NL	[-20 ;16]	[-2 ; 0.8]	[-120 ; -48]
Negative Small	NS	[-12 ; 0]	[-1.2; 0]	[-72 ; 0]
Zero	ZE	[-16 ;16]	[-0.4;0.4]	[-24 ; +24]
Positive Small	PS	[0 ; 12]	[0 ; 1.2]	[0 ; 66]
Positive Large	PL	[8 ; 20]	[0.8 ; 2]	[48 ; 120]

B. Rule base and inference matrix:

For the inference method, there are too many methods, and the most applied is the Max-min method, the inference matrix of the fuzzy controller is given in the Table 2.

TABLE II. INFERENCE MATRIX OF THE FUZZY CONTROLLER

E \ ΔE	NL	NS	ZE	PS	PL
NL	NL	NL	NL	NS	ZE
NS	NL	NL	NS	ZE	ZE
ZE	NL	NS	ZE	PS	PL
PS	ZE	ZE	PS	PS	PL
PL	ZE	ZE	PL	PL	PL

C. Defuzzification:

When the fuzzy outputs are computed, they must be transformed into a numerical value. There are several methods of defuzzification, and in this study the method used is the center of gravity.

IV. CONTROL OF ASYNCHRONOUS MACHINE USING THE ARTIFICIAL NEURAL NETWORK:

A neural network is composed of several simple elements called neurons working in parallel. By adjusting the values of the connections (or weights) between the elements (neurons), we can train a neural network for a specific task. The ANN are used in many important engineering and scientific applications, some of these are: signal enhancement, noise cancellation, pattern classification, system identification, prediction, and control [3] .

Neural network learning depends on the network architecture and the nature of the problem and there are many learning rules, which are divided to a supervised learning, none supervised learning and learning by reinforcement [3]. The general principle of learning algorithms is based on the minimization of a cost function which can be defined as the quadratic of the differences between the outputs of the network and values desired [8][9] as it is shown on the figure 3.

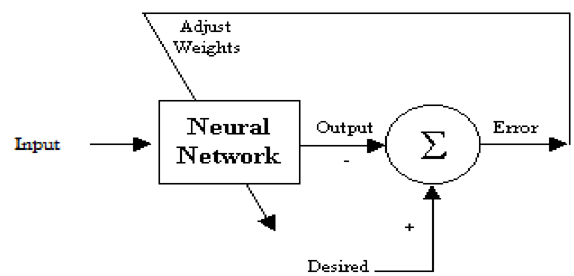

Fig. 3. Learning principle of neural networks

To control the asynchronous machine with a neural controller, it had chosen to work with the block “NARMA-L2 (Feedback Linearization) Control”, given its ease of use and the results and performances that presents. The block "" NARMA-L2 "or “Nonlinear Autoregressive-Moving Average "is a block that converts a nonlinear system to a linear one, for that our block involves first the identification of the system to control [4]. To identify a system there are many methods, that we can find the regression algorithm with a graded step, the genetic algorithm based approach with its binary representation and the approach based on the combination of the genetic algorithm in its real representation and the artificial neural network with a polynomial activation function [5] and it’s based in this study on the last approach. After identifying system’s model to monitor, we train a neural network in order to make the system output follows the reference input. Then we choose the architecture of the network, for that it had been chosen a network with eight neurons in the hidden layer, and the learning algorithm chosen is Levenberg Marquard seen its accuracy and quick convergence .

V. SIMULATION RESULTS

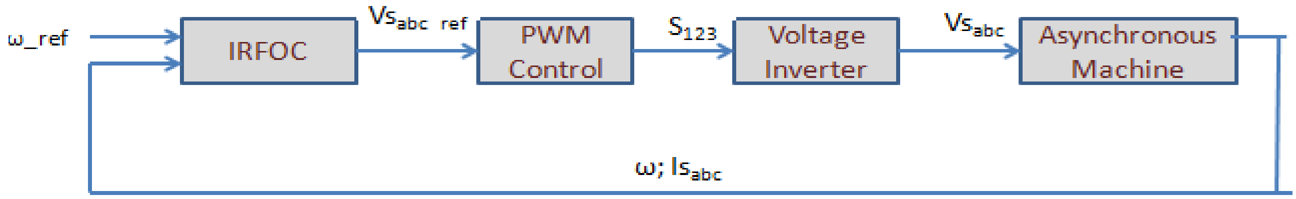

Fig. 4. Induction motor associated with the control chain

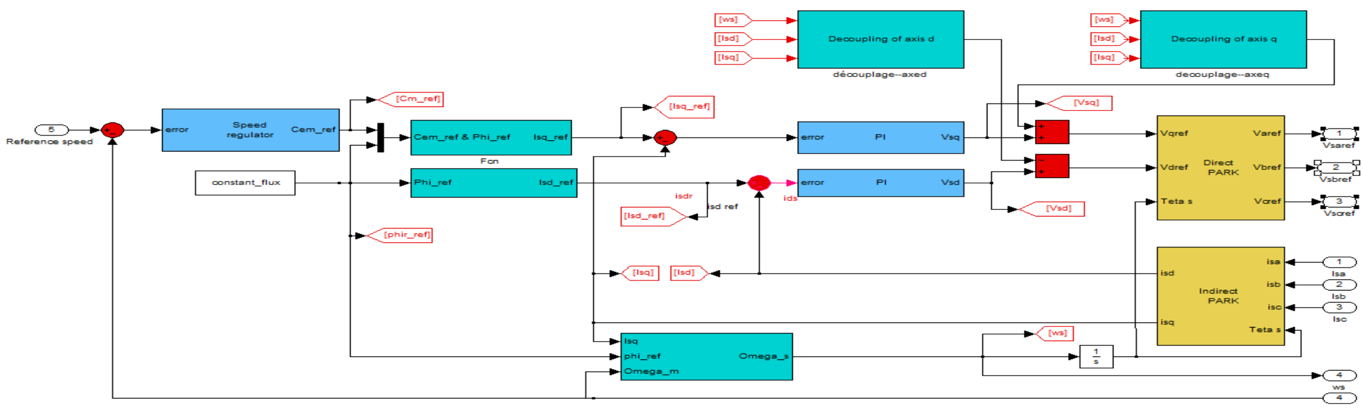

Fig. 5. IRFOC for induction motor drive

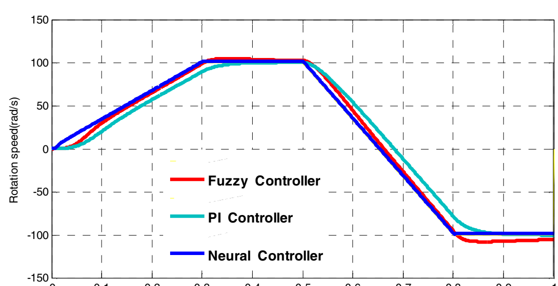

Fig. 6. Rotation speed of the three commands

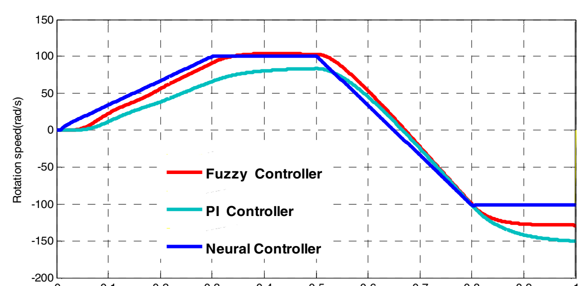

Fig. 7. Rotation speed of the three commands under a variable load torque

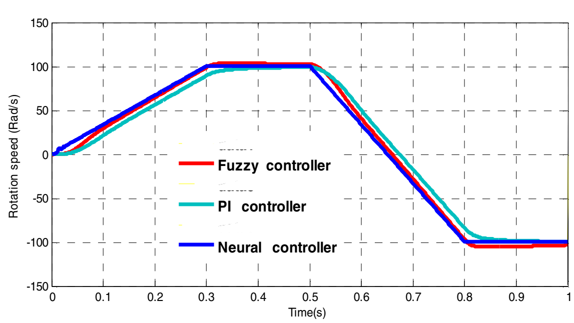

Fig. 8. Rotation speed for Rr=2*Rrn

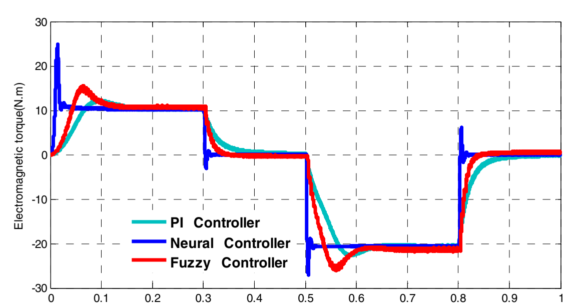

Fig. 9. Electromagnetic torque for Rr=2*Rrn

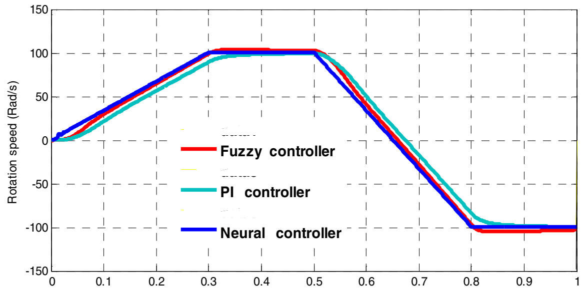

Fig. 10. Rotation speed for J=2*Jn

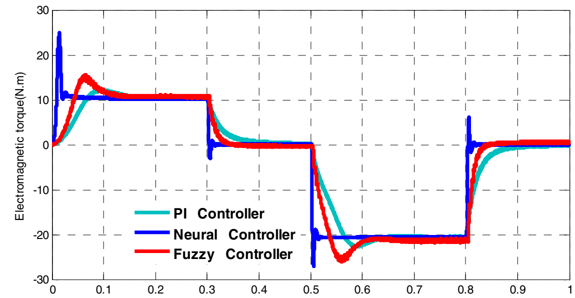

Fig. 11. Electromagnetic torque for J=2*Jn

VI. INTERPRETATION OF SIMULATION RESULTS AND DISCUSSION:

The simulation results present the response of the system following a trapezoidal set point and they are performed for a simulation time t= 1 s. The figure 6 shows the rotation speed of the three commands with no load, and the figure 7 shows the response of the three techniques of control during the application of a resisting variable torque applied at the following:

$$Cr = \begin{cases} 15t \ \text{N.m} & \text{for} \quad 0\,\text{s} < t < 0.3\,s \\ 15 \ \text{N.m} & \text{for} \quad 0.3\,\text{s} < t < 0.5\,s \\ 50t \ \text{N.m} & \text{for} \quad 0.5\,\text{s} < t < 0.8\,s \\ 50 \ \text{N.m} & \text{for} \quad 0.8\,\text{s} < t < 1\,\text{s} \end{cases}$$

The figures: 8, 9, 10 and 11 show the rotation speed and the electromagnetic torque during the parametric variation and rotation inversion at t=0.5 s. In the figures 8 and 9, the rotor resistance was increased to 100% over the nominal value whereas in the figures 10 and 11 the moment of inertia was raised to 100%. From the simulation results we notice that the speed of the machine follows its reference and remains stable at the desired value even during application of the load variable torque. With a reversal of the direction of rotation, and with application of a parametric variation for the rotor resistance (+100%) and the moment of inertia for up to 100%, speed changes direction and well-maintained at the desired value.

TABLE III. PERFORMANCES FOR RR=2*RRN

Command / Performance	PI	FUZZY	NEURAL
Speed error (%) $\mathbf{0\,s < t < 0.3\,s}$	10.7	3.5	0.1
Response time(s) $\mathbf{0.3\,s < t < 0.5\,s}$	0.15	0.02	0.001
Speed error (%) $\mathbf{0.5s < t < 0.8\,s}$	17	6.5	0.12

TABLE IV. PERFORMANCES FOR A LOAD VARIABLE TORQUE

Command / Performance	PI	Fuzzy	Neural
Speed error(%) $\mathbf{0\,s < t < 0.3\,s}$	18.5	7	0.004
Response time(s) $\mathbf{0.3\,s < t < 0.5\,s}$	0.2	0.16	0.005
Speed error(%) $\mathbf{0.5s < t < 0.8\,s}$	15	6	0.006

The table 3 and 4 show the performances of the system to a trapezoidal set point when the machine is affected by internal and external disturbances The internal and external disturbances are summed up respectively by the increase of rotor resistance (+100% Rr), and a variable load torque. From the table 3 and 4 we see that the intelligent controllers present good performances in comparison with the conventional controller during the parametric variation and we can see also that the neural controller remains the fastest during a set point changing and it presents a high accuracy during acceleration and deceleration, and a less sensitivity to uncertainties disturbances.

VII. CONCLUSION:

The asynchronous machine is a non linear system affected by parameters variation and unknown disturbances .This paper deals with a contribution to induction machine's intelligent control. The work was done in the form of a comparative study between conventional controller and intelligent controllers; it reveals the motivation to realize researches in the field of control by artificial intelligence techniques to the asynchronous machine drive.

It is concluded that the neural controller had a good performances face to parametric variations and to unknown disturbances comparing to the other techniques of control. , for that it can be applied for the electric vehicle motorization and automation. It is advisable to examine experimentally the efficiency of neural controller performances to confirm the results found by this study.

VIII. APPENDIX:

SYMBOL	QUANTITY	NUMERICAL APPLICATION
Rs	Stator resistance	4.85 Ω
Rr	Rotor resistance	3.805 Ω
Ls	Stator inductance	0.274 H
Lr	rotor inductance	0.274 H
J	Moment of inertia	0.031 kg.m²;
f	coefficient of friction	0.00114 kg.m²/s
P	Pole pairs	2
M	Mutual inductance	0.258 H
Kp	Proportional controller gain for current regulation	0.0932 (H/s)
Ki	integral controller gain for current regulation	145.5 (R/s)
Kp	Proportional controller gain for speed regulation	0.93 (Kg.m²/s)
Ki	integral controller gain for speed regulation	0.0342 (Kg.m²/s²)

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