



# DIRECT TORQUE CONTROL FOR INDUCTION MOTOR USING INTELLIGENT TECHNIQUES

R.Toufouti S.Meziane ,H. Benalla

Laboratory of Electrical Engineering University Constantine Algeria  
[[toufoutidz.mezianedz\\_Benalladz@yahoo.fr](mailto:toufoutidz.mezianedz_Benalladz@yahoo.fr)]

## ABSTRACT

In this paper, we propose two approach intelligent techniques of improvement of Direct Torque Control (DTC) of Induction motor such as fuzzy logic (FL) and artificial neural network (ANN), applied in switching select voltage vector .The comparison with conventional direct torque control (DTC), show that the use of the DTC\_FL and DTC\_ANN, reduced the torque, stator flux, and current ripples. The validity of the proposed methods is confirmed by the simulative results.

**Keywords:** *Fuzzy inference system (FIS); Fuzzy logic, direct torque control (DTC), induction motor, artificial neural network (ANN).*

## 1. INTRODUCTION

Induction motor drives controlled by Field Oriented control (FOC) [1] have been till now employed in high performance industrial applications, has achieved a quick torque response, and has been applied in various industrial applications instead of dc motors [1]-[22].It permit independent control of the torque and flux by decoupling the stator current into two orthogonal components FOC, however, is very sensitive to flux, which is mainly affected by parameter variations. It depends on accurate parameter identification to achieve the expected performance. During the last decade a new control method called DTC (Direct Torque Control) has been developed for electrical machines[1]-[22].TC principles were first introduced by Depenbrock [1] and Takahashi [2]. In this method, Stator voltage vectors is selected according to the differences between the reference and actual torque and stator flux linkage. The DTC method is characterised by its simple implementation and a fast dynamic response. Furthermore, the inverter is directly controlled by the algorithm, i.e. a modulation technique for the inverter is not needed [1]-[7].However if the control is implemented on a digital system (which can be considered as a standard nowadays), the actual values of flux and torque could cross their boundaries too far. The main advantages of DTC are absence of

coordinate transformation and current regulator; absence of separate voltage modulation block, Common disadvantages of conventional DTC are high torque ripple and slow transient response to the step changes in torque during start-up[1]-[4]. For that reason the application of Fuzzy logic and artificial neural network attracts the attention of many scientists from all over the world [1]. The reason for this trend is the many advantages which the architectures of ANN have over traditional algorithmic methods [8]-[22]. .

Among the advantages of ANN are the ease of training and generalization, simple architecture, possibility of approximating nonlinear functions, insensitivity to the distortion of the network, and inexact input data [8]-[14] [17].[20].In this paper we present the evaluation of flux and torque using the three stator currents is the voltage of input inverter, and Fuzzy logic and artificial neural network has been devised having as inputs the torque error, the stator flux error and the position of the stator flux in which it lies, and as output the voltage space vector to be generate by the inverter[8]-[13],[17].The ANN then replaces the switching table'. The theoretical Principle, numerical simulation procedures and the results of these methods are discussed and compared with conventional DTC (C\_DTC).

## 2. DIRECT TORQUE CONTROL WITH TWO-LEVEL INVERTER

Fig. 1 shows the schematic of The basic functional blocks used to implement the DTC of

induction motor drive. A voltage source inverter (VSI) supplies the motor and it is possible to control directly the stator flux and the electromagnetic torque by the selection of optimum inverter switching modes [1]-[4].

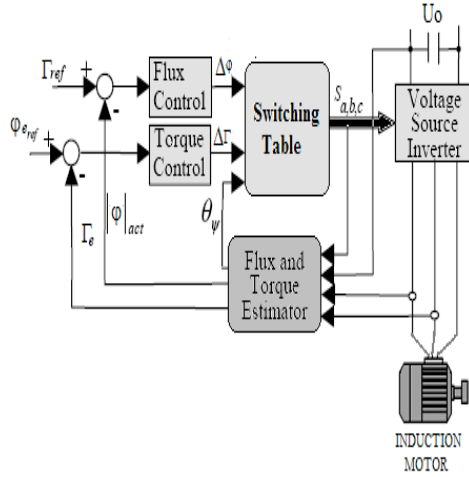


Figure 1. Basic direct torque control scheme for ac motor drives

### 2.1. Vector Model of Inverter Output Voltage

In the PWM voltage source inverters, considering the combinations of the states of switching functions inverter switching state functions ( $C_1, C_2, C_3$ ) which can take either 1 or 0, the voltage vector becomes:

$$V_s = \sqrt{\frac{2}{3}} U_0 \left[ C_1 + C_2 e^{j\frac{2\pi}{3}} + C_3 e^{j\frac{4\pi}{3}} \right] \quad (1)$$

Eight switching combinations can be taken according to the above relationship: two zero voltage vectors and six non-zero voltage vectors show by Fig.2 [1][2].

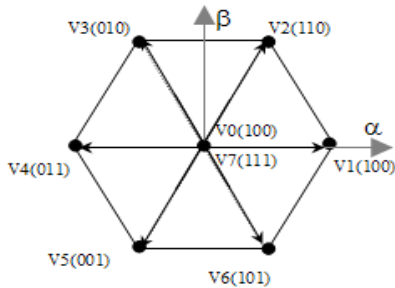


Figure 2. Partition of the  $\alpha\beta$  plane into 6 angular sectors

### 2.2. Stator Flux and Torque Estimation

The components of the current ( $I_{s\alpha}, I_{s\beta}$ ), and stator voltage ( $V_{s\alpha}, V_{s\beta}$ ) are obtained by the

application of the transformation given by (5) and (6), [1] :

$$\begin{cases} I_{s\alpha} = \sqrt{\frac{2}{3}} I_{sa} \\ I_{s\beta} = \frac{1}{\sqrt{2}} (I_{sb} - I_{sc}) \end{cases} \quad (5)$$

$$\begin{cases} V_{s\alpha} = \sqrt{\frac{2}{3}} U_0 \left( C_1 - \frac{1}{2} (C_2 + C_3) \right) \\ V_{s\beta} = \frac{1}{\sqrt{2}} U_0 (C_2 - C_3) \end{cases} \quad (6)$$

The components of the stator flux ( $\varphi_{s\alpha}, \varphi_{s\beta}$ ) given by (7).

$$\begin{cases} \overline{\varphi}_{s\alpha} = \int_0^t (\overline{V}_{s\alpha} - R_s \overline{I}_{s\alpha}) dt \\ \overline{\varphi}_{s\beta} = \int_0^t (\overline{V}_{s\beta} - R_s \overline{I}_{s\beta}) dt \end{cases} \quad (7)$$

The stator flux linkage phase is given by (8).

$$\varphi_s = \sqrt{\varphi_{s\alpha}^2 + \varphi_{s\beta}^2} \quad (8)$$

The electromagnetic couple be obtained starting from the estimated sizes of flux ( $\varphi_{s\alpha}, \varphi_{s\beta}$ ) and calculated sizes of the current,  $I_{s\alpha}, I_{s\beta}$ )

$$\Gamma_{em} = p (\varphi_{s\alpha} I_{s\beta} - \varphi_{s\beta} I_{s\alpha}) \quad (9)$$

The stator resistance  $R_s$  can be assumed constant during a large number of converter switching periods  $T_e$ . The voltage vector applied to the induction motor remains also constant one period  $T_e$ . Therefore, resolving first equation of system leads to:

$$\overline{\varphi}_s = \int_0^t (\overline{V}_s - R_s \overline{I}_s) dt \quad (10)$$

$$\overline{\varphi}_s(t) \approx \overline{\varphi}_{s0} + \overline{V}_s T_e \quad (11)$$

In equation (11);  $\varphi_{s0}$  stands for the initial stator flux condition. This equation shows that when the term  $R_s I_s$  can be neglected, (in high speed operating condition for example), the extremity of stator flux vector  $V_s$ . Furthermore, the



The angle of flux linkage  $\theta_s$  is an angle between stator's flux  $\phi_s$  and a reference axis is defined by equation (14):

$$\theta_s = \arctan \frac{\phi_{\beta s}}{\phi_{\alpha s}} \quad (14)$$

in equation 3  $\phi_{s\alpha}$  and  $\phi_{s\beta}$  are the component of flux linkage  $\phi_s$  in the plan  $(\alpha, \beta)$  on the basis of voltage vector shown as Fig.2, fuzzy variable may be described by 12 language value ( $\theta_1 \rightarrow \theta_{12}$ ), it's the membership function's distribution is shown Fig.6 [9].

### 3.4. Voltage Vectors $U_i$

For the voltage vectors  $U_i (i=0-6)$ , the membership distribution function of  $U_i$  is given by Fig.7.

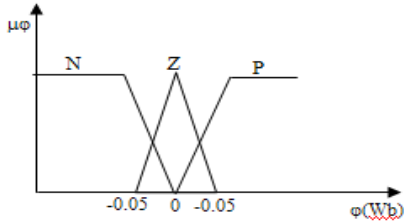


Figure 4. Membership functions for flux error

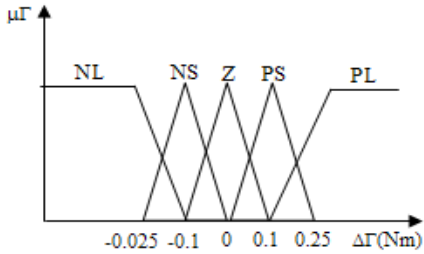


Figure 5. Membership functions for flux error

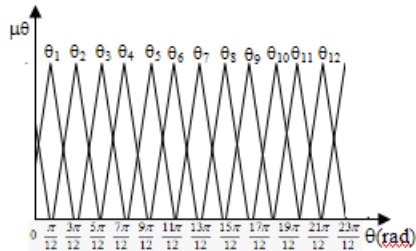


Figure 6. Membership functions for flux error

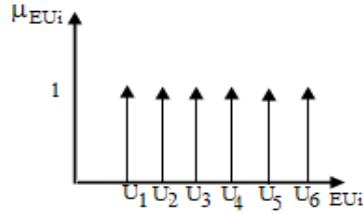


Figure 7. Membership functions for flux error

### 5.2. The Control Variable

Each control rule can be described using the state variables  $\Delta\phi$ ,  $\Delta\Gamma$ ,  $\theta_s$  and  $U$ . The  $i^{th}$  rule  $R_i$  can be written as:

$R_i$  : if  $\Delta\phi$  is  $A_i$ ,  $\Delta\Gamma$  is  $B_i$  and  $\theta_s$  is  $C_i$  then  $n$  is  $N_i$

The membership functions of variables  $A$ ,  $B$ ,  $C$  and  $N$  are given by  $\mu_A$ ,  $\mu_B$ ,  $\mu_C$  and  $\mu_N$  respectively. The weighting factor  $\alpha_i$  for  $i^{th}$  rule can be written as [9][10][13].

$$\alpha_i = \min(\mu_{A_i}(\Delta\phi), \mu_{B_i}(\Delta\Gamma), \mu_{C_i}(\Delta\theta_s)) \quad (15)$$

By fuzzy reasoning, Mamdani's minimum procedure [9]

gives :

$$\mu'_{N_i}(n) = \min(\alpha_i, \mu_{N_i}(n)) \quad (16)$$

The membership function  $\mu_N$  of the output  $n$  is point given by:

$$\mu_N(n) = \max_{i=1}^{180}(\alpha_i, \mu'_{N_i}(n)) \quad (17)$$

$$\mu_{Nout}(n) = \max_{i=1}^7(\mu_{Nout}(n)) \quad (18)$$

According to the all rules and mamdani's organ, and all the variable membership function, a fuzzy control have 180 table can gain, as shown table2 [9], The fuzzy control table be queried in real time, deposited the table into memory of microcomputer.



4. DTC BASED NEURAL NETWORK

Principles of Artificial Neural Networks

Artificial neural networks use a dense interconnection of computing nodes to approximate nonlinear functions [19][20]. Each node constitutes a neuron and performs the multiplication of its input signals by constant weights, sums up the results and maps the sum to a nonlinear activation function  $g$ ; the result is then transferred to its output. A feed forward ANN is organized in layers: an input layer, one or more hidden layers and an output layer. A MLP consists of an input layer, several hidden layers, and an output layer [15]-[22]. Node  $i$ , also called a neuron, in a MLP network is shown in Fig.8. It includes a summer and a nonlinear activation function  $g$ .

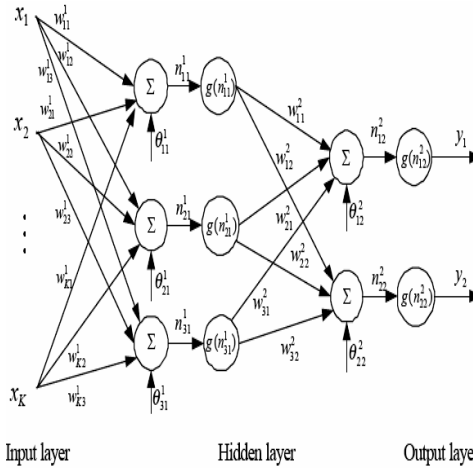


Fig 8. A multilayer perceptron network with one hidden layer.

The inputs  $x_k, k = 1...K$  to the neuron are multiplied by weights  $w_{ki}$  and summed up together with the constant bias term  $\theta_i$ . The resulting  $i n$  is the input to the activation function  $g$ . The activation function was originally chosen to be a relay function, but for mathematical convenience a hyperbolic tangent ( $\tanh$ ) or a sigmoid function are most commonly used [15] [22].

The mathematical model of a neuron is given by (19):

$$y_i = g_i = g \left( \sum_{i=1}^N w_{ji} \cdot x_j + \theta_i \right) \quad (19)$$

4.2. Simulation Model and Structure of DTC System Based ANN

The ANN is trained by a learning algorithm which performs the adaptation of weights of the network iteratively until the error between target vectors and the output of the ANN is less than an error goal. The most popular learning algorithm for multilayer networks is the backpropagation algorithm and its variants [19]. The latter is implemented by many ANN software packages such as the neural network toolbox from MATLAB [19] [20].

In the case presented in this paper the DTC control strategy shown on table I has been implemented. Neural network has been devised having as inputs the torque error, the stator flux error and the position of the stator flux, and as output the voltage space vector to be generate by the inverter [17]. The ANN block then replaces the switching table selector block of Fig.9.

		$\theta_1$					$\theta_2$						
$\Delta\sigma$	$\Delta\Gamma$	PL	PS	Z	NS	NL	$\Delta\sigma$	$\Delta\Gamma$	PL	PS	Z	NS	NL
P	V6	V1	V0	V2	V2	P	V6	V6	V0	V1	V2		
Z	V6	V6	V0	V0	V3	Z	V5	V5	V0	V0	V2		
N	V5	V5	V0	V4	V3	N	V5	V4	V0	V3	V3		

		$\theta_3$					$\theta_4$						
$\Delta\sigma$	$\Delta\Gamma$	PL	PS	Z	NS	NL	$\Delta\sigma$	$\Delta\Gamma$	PL	PS	Z	NS	NL
P	V5	V6	V0	V1	V1	P	V5	V5	V0	V6	V1		
Z	V5	V5	V0	V0	V2	Z	V4	V4	V0	V0	V1		
N	V4	V4	V0	V3	V2	N	V4	V3	V0	V2	V2		

		$\theta_5$					$\theta_6$						
$\Delta\sigma$	$\Delta\Gamma$	PL	PS	Z	NS	NL	$\Delta\sigma$	$\Delta\Gamma$	PL	PS	Z	NS	NL
P	V4	V5	V0	V6	V6	P	V4	V4	V0	V5	V6		
Z	V4	V4	V0	V0	V1	Z	V3	V3	V0	V6	V2		
N	V3	V3	V0	V2	V1	N	V3	V2	V0	V1	V1		

		$\theta_7$					$\theta_8$						
$\Delta\sigma$	$\Delta\Gamma$	PL	PS	Z	NS	NL	$\Delta\sigma$	$\Delta\Gamma$	PL	PS	Z	NS	NL
P	V3	V4	V0	V5	V5	P	V3	V3	V0	V4	V5		
Z	V3	V3	V0	V0	V6	Z	V2	V2	V0	V0	V5		
N	V2	V2	V0	V1	V6	N	V2	V1	V0	V6	V6		

		$\theta_9$					$\theta_{10}$						
$\Delta\sigma$	$\Delta\Gamma$	PL	PS	Z	NS	NL	$\Delta\sigma$	$\Delta\Gamma$	PL	PS	Z	NS	NL
P	V2	V3	V0	V4	V4	P	V2	V2	V0	V3	V4		
Z	V2	V2	V0	V0	V5	Z	V1	V1	V0	V0	V4		
N	V1	V1	V0	V6	V5	N	V1	V6	V0	V5	V5		

		$\theta_{11}$					$\theta_{12}$						
$\Delta\sigma$	$\Delta\Gamma$	PL	PS	Z	NS	NL	$\Delta\sigma$	$\Delta\Gamma$	PL	PS	Z	NS	NL
P	V1	V2	V0	V3	V3	P	V1	V1	V0	V2	V3		
Z	V1	V1	V0	V0	V4	Z	V6	V6	V0	V0	V3		
N	V6	V6	V0	V5	V4	N	V6	V5	V0	V4	V4		

Table 2. Fuzzy logic rules

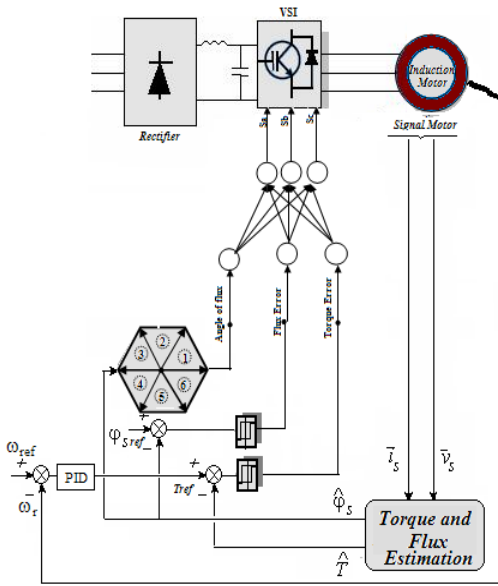


Fig 9. Basic direct torque control scheme based ANN

To create the block ANN switching table we passed by this program Matlab.

```
%P inputs
(E_TORQUE, E_FLUX, E_POSITION)
p=[0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1;0
0 0 0 0 0 1 1 1 1 1 1 0 0 0 0 0 0 1 1 1 1 1 1;1 2 3 4
5 6 1 2 3 4 5 6 1 2 3 4 5 6 1 2 3 4 5 6];
% vector output of state
Sa, Sb, Sc.
t=[0 1 0 1 0 1 0 0 0 1 1 1 1 0 1 0 1 0 1 0 0 0 1 1;0
1 0 1 0 1 1 1 0 0 0 1 1 0 1 0 1 0 1 1 1 1 0 0 0;0 1 0 1
0 1 0 1 1 1 0 0 1 0 1 0 1 0 0 0 1 1 1 0];
net10 = newff([0 1;0 1;1 6],[10 3],{'tansig'
'purelin'});
net10.trainParam.epochs = 1000;
net10.trainParam.goal=0;
net10 = train(net10,p,t);
Y = sim(net10,p); e=t-Y; plot(p,t,p,Y,'o')
```

The training ANN is given by Fig.10

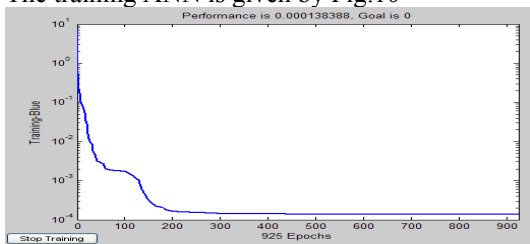


Fig 10. The training ANN

In Matlab command we generate the Simulink block ANN of switching table by '**gensim (net10)**' given this model show Fig11

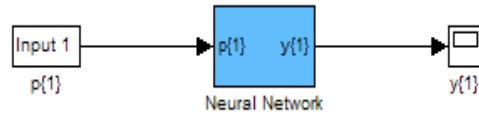


Fig 11. Simulink block for ANN switching table

The block neural network content two layer 1 and 2 show Fig.12

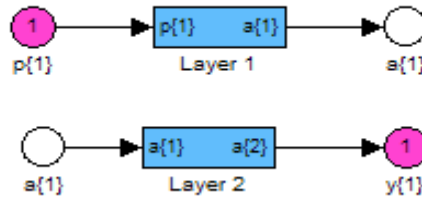


Fig 12. Block neural network

Where the Layer1 and Layer2 given by Fig.13

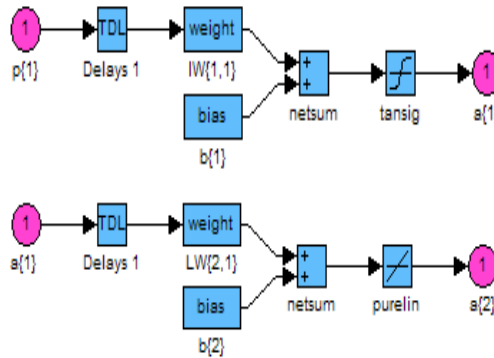


Fig 13. Block Layer1 and Layer2

## 6. INTERPRETATION RESULTS

To study the performance of the fuzzy logic and neural network switching table with direct torque control strategy, the simulation of the system was conducted using SIMULINK and Fuzzy Logic Toolbox.

Simulation results for a DTC system when controlling the induction machine is following parameters:

$P_N = 3KW$  ,  $V_n = 230V$  ,  $f_N = 60Hz$  ,  $R_s = 2.89\Omega$  ,  $R_r = 2.39\Omega$  ,  $P = 2$  ,  $L_s = L_r = 0.225H$  ,  $L_m = 0.214H$  ,  $J = 0.005kgm^2$ . 3KW.

The Sampling period of the system is  $50\mu s$ . To compare with C\_DTC, FLDTTC and ANN\_DTC for IM are simulated. In two cases, the dynamic responses of speed, flux, torque and stator current for the starting process with  $[5 \rightarrow 7 \rightarrow 3]$  Nm load torque applied and a constant command flux of  $0.6Wbs$  are shown in Figure from 14 to 17 respectively. Figs.14 (a, b and c) show the response of electric torque of the C\_DTC, FL\_DTC and ANN\_DTC respectively. It can be seen that the ripple in torque with FL\_DTC and ANN\_DTC control is less than  $0.3 Nm$  and with conventional direct torque control the ripple is about  $2 Nm$  at the same operating conditions. Figs.15 (a, b and c) show the response of stator flux magnitude of the C\_DTC, FLDTTC and ANN\_DTC respectively. By FLDTTC and ANN\_DTC technique shown Fig15 (b and c), the stator flux are the fast response in transient state and the ripple in steady state is reduced remarkably compared with conventional DTC, the flux changes through big oscillation and the torque ripple is bigger in C\_DTC shown Fig15a. Fig16 (a, b and c), It can be noticed that stator flux vector describes a trajectory almost circular. Figs .17(b and c) show the steady state current response of the FLDTTC and ANN\_DTC has negligible ripple in stator current and a nearly sinusoidal wave form while as with conventional DTC the stator current has considerably very high ripple.

## 7. CONCLUSION

In this paper a FLDTTC and ANN\_DTC of induction machine have been proposed. An improved torque and flux response was achieved with the FLDTTC and ANN\_DTC than the conventional DTC. The performance has been tested by simulations. Also, a command flux optimization scheme has been proposed to reduce the torque ripple. The optimization was tested using simulation. The results show a reasonable improvement by flux optimization. The main improvements shown are:

- Reduction of torque and current ripples in transient and steady state response.
- No flux droppings caused by sector changes circular trajectory.
- Fast stator flux response in transient state.

## 8. SIMULATION RESULTS

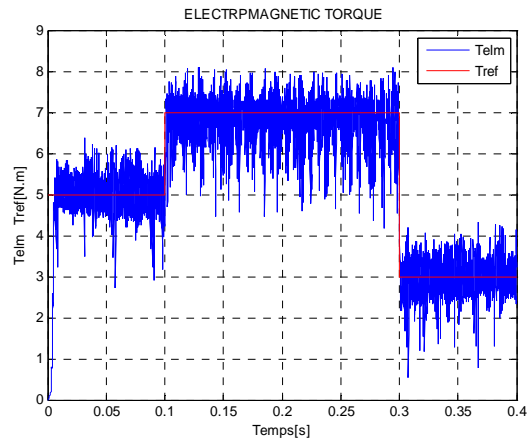


Fig.14a. Electromagnetic torque Response C DTC

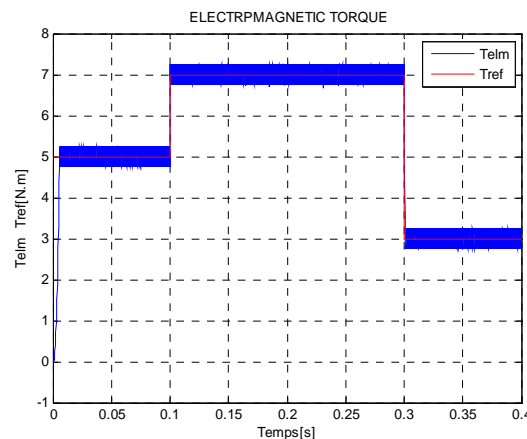


Fig.14b. Electromagnetic torque Response FL DTC

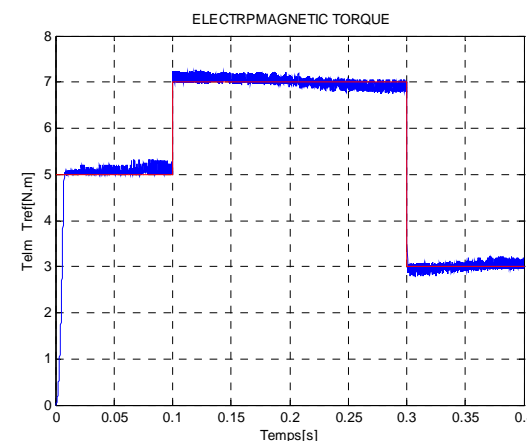


Fig.14c. Electromagnetic torque Response ANN DTC

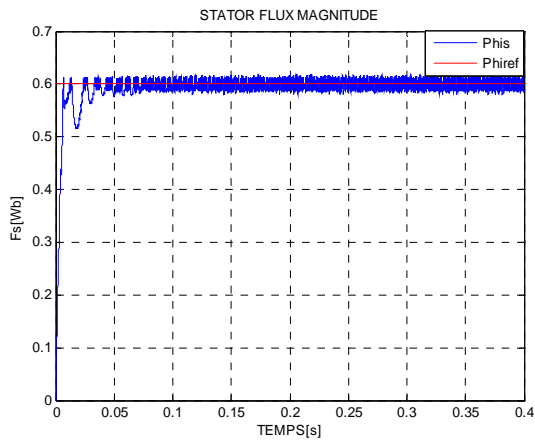


Fig. 15a. The stator flux Magnitude C\_DTC

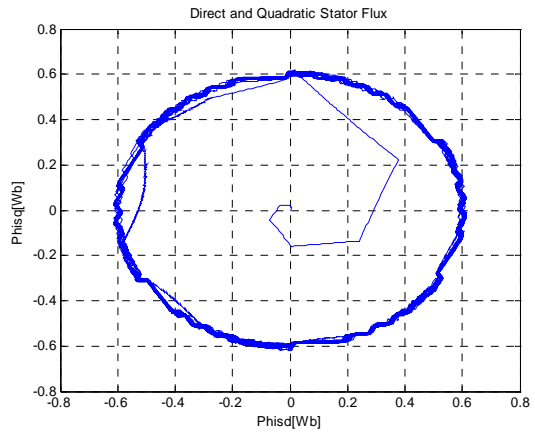


Fig. 16a. Direct and quadratic stator flux C\_DTC

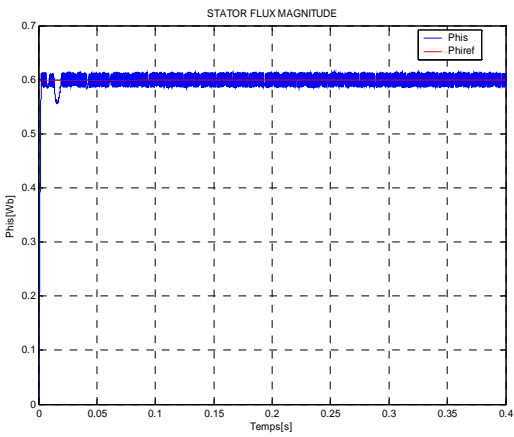


Fig. 15b. The stator flux Magnitude FL DTC

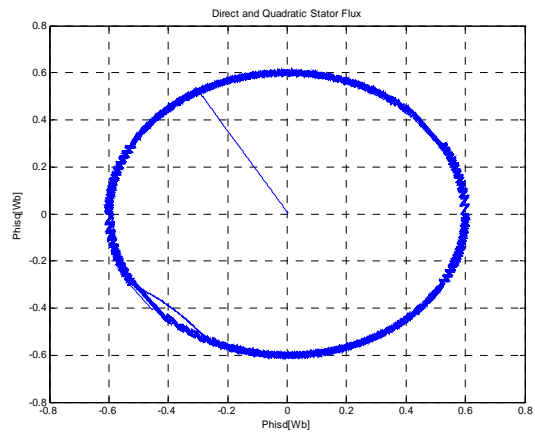


Fig. 16b. Direct and quadratic stator flux FL DTC

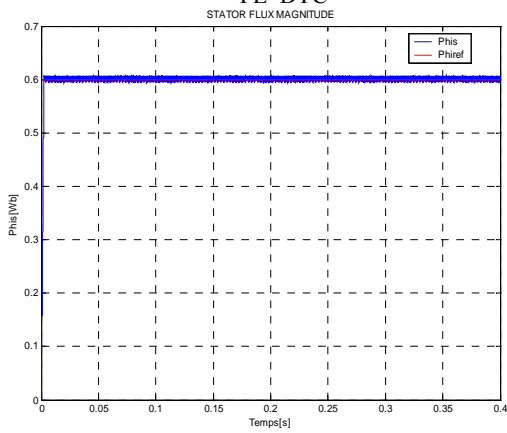


Fig. 15c. the stator flux Magnitude ANN DTC

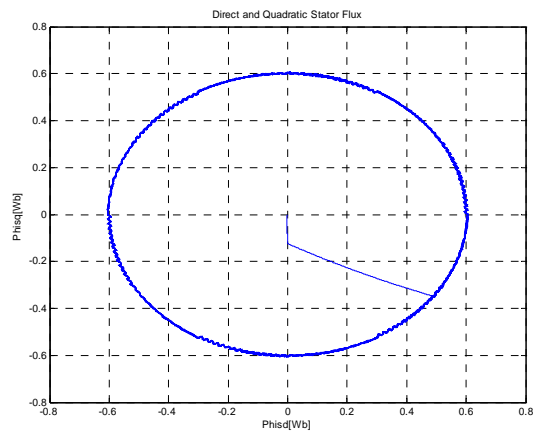


Fig. 16c. Direct and quadratic stator flux ANN DTC

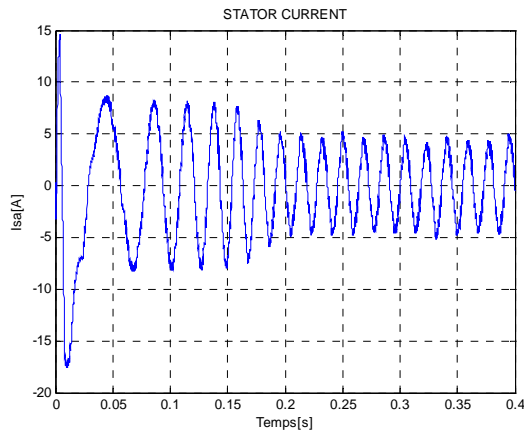


Fig.17a. the stator current C\_DTC

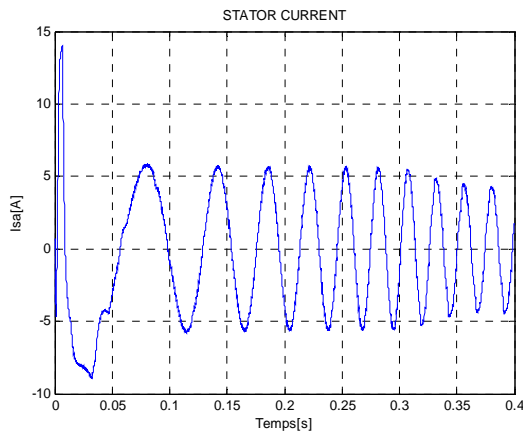


Fig.17b. the stator current FL\_DTC

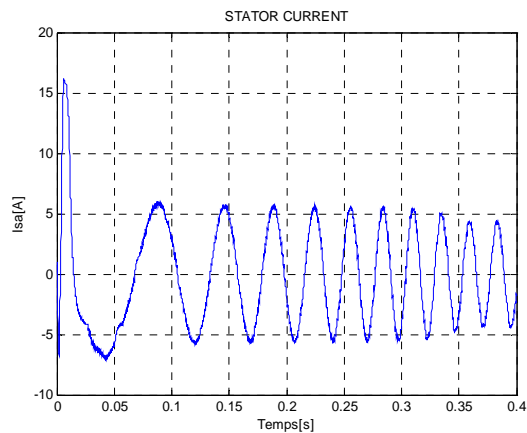


Fig.17c. the stator current ANN DTC

## 9. REFERENCES

- [1]. Takahashi, T. Noguchi, "A new quick-response and high-efficiency control strategy of induction motor", IEEE Trans. On IA, Vol.22, N°.5, Sept/Oct 1986, PP.820-827.
- [2]. M. Depenbrock, "Direct self – control (DSC) of inverter – fed induction machine", IEEE Trans. Power Electronics, Vol.3, N°.4, Oct 1988, PP.420-829.
- [3]. D. Casadei, F. Profumo, G.Serra and A.Tani, "FOC and DTC: Tox Viable Schemes for induction Motors Torque Control", IEEE Trans. Power Electronics. On PE, Vol.17, N°.5, Sept2002,
- [4]. D. Casadei and G.Serra, "Implementation of direct Torque control Algorithmes for Induction Motors Based On Discrete Space Vector Modulation", IEEE Trans. Power Electronics. Vol.15, N°.4, JULY2002,
- [5]. A.A.Pujol, "Improuvment in direct torque control of induction Motors", Thèse de doctorat de L'UPC, Novembre2000
- [6]. R.Toufouti ,H.Benalla, and S.Meziane "Three-Level Inverter With Direct Torque Control For Induction Motor", World Conference on Energy for Sustainable Development: Technology Advances and Environmental Issues, Pyramisa Hotel Cairo - Egypt, 6 - 9 December 2004.
- [7]. JIA-QIANG YANG, JIN HUANG " A New Full-Speed Range Direct Torque Control Strategy for Induction Machine", Proceedings of the Third International Conference on Machine Learning and Cybernetics, Guangzhou, 26-29 August 2004.
- [8]. R.Toufouti S.Meziane ,H. Benalla, "Direct Torque Control for Induction Motor Using Fuzzy Logic" *ICGST Trans. on ACSE*, Vol.6, Issue 2, pp. 17-24, June, 2006.
- [9]. Jia-Qiang Yang, Jin Huang, "Direct Torque Control System for Induction Motors With Fuzzy Speed Pi Regulator" Proceedings of the Fourth International Conference on



- Machine Learning and Cybernetics, Guangzhou, 18-21 August 2005.
- [10]. Hui-Hui Xia<sup>0</sup>, Shan Li, Pei-Lin Wan, Ming-Fu Zhao, "Study on Fuzzy Direct Torque Control System", Proceedings of the Fourth International Conference on Machine Learning and Cybernetics, Beijing, 4-5 August 2002.
- [11]. Ji-Su Ryu, In-Sic Yoon, Kee-Sang Lee and Soon-Chan Hong, "Direct Torque Control of Induction Motors Using Fuzzy Variables witching Sector", Industrial Electronics, 2001. Proceedings. ISIE 2001. IEEE International Symposium on Volume 2, Issue, 2001 Page(s):901 - 906 vol.2
- [12]. Sayeed A. Mir, Malik E. Elbuluk and Donald S. Zinger, "Fuzzy Implementation of Direct Self Control of Induction Machines", IEEE Transactions On Industry Applications, Vol. 30, No. 3, May June 1994 129
- [13]. Yang Xia and Oghanna, W. "Fuzzy Direct Torque Control of Induction Motor with Stator Flux estimation Compensation", Industrial Electronics, Control and Instrumentation, 1997. IECON 97. 23rd International Conference on Volume 2, Issue, 9-14 Nov 1997 Page(s):505 - 510 vol.2
- [14]. Yang Xia and Oghanna, W "Study on fuzzy control of induction machine with direct torque control approach," Industrial Electronics, 1997. ISIE apos;97., Proceedings of the IEEE International Symposium on Volume 2, Issue, 7-11 Jul 1997 Page(s):625 - 630 vol.2
- [15]. Miroslaw Wlas, Zbigniew Krzemin'ski, Jaroslaw Guzin'ski, Haithem Abu-Rub and Hamid A. Toliyat, "Artificial-Neural-Network-Based Sensorless Nonlinear Control of Induction Motors" IEEE Transactions On Energy Conversion, Vol. 20, No. 3, September 2005
- [16]. Luis A. Cabrera, Malik E. Elbuluk and Iqbal Husain, "Tuning the Stator Resistance of Induction Motors Using Artificial Neural Network" IEEE ransactions On Power Electronics, Vol. 12, No. 5, September 1997
- [17]. Cirrincione, G, Cirrincione, M, Chuan Lu and Pucci, M, " Direct Torque Control o Induction Motors By Use of The GMR Neural Network" Neural Networks, 2003. Proceedings of the International Joint Conference on Volume 3, Issue, 20-24 July 2003 Page(s): 2106 - 2111 vol.3
- [18]. Xuezhi Wu and Lipei Huang, "Direct Torque Control of Three-Level Inverter Using Neural Networks as Switching Vector Selector" Industry Applications Conference, 2001. Thirty-Sixth IAS Annual Meeting. Conference Record of the 2001 IEEE Volume 2, Issue, 30 Sep-4 Oct 2001 Page(s):939 - 944 vol.2
- [19]. Ghouili, J and Cheriti, A" Induction motor dynamic neural stator flux estimation using active and reactive power for direct torque control." Power Electronics Specialists Conference, 1999. PESC 99. 30th Annual IEEE Volume 1, Issue, Aug 1999 Page(s):501 - 505 vol.
- [20]. A. Ba-razzouk, A. Cheriti and G. Olivier, "A Neural Networks Based Field Oriented Control Scheme For Induction Motor "IEEE Industry Applications Society Annual Meeting New Orleans, Louisiana, October 5-9, 1997
- [21]. Chengzhi Cao, Mu-Ping Lu and Xin Wang, "Speed Estimation And Stimulation Of Dtc System Based On Wavelet Neural Network "Proceedings of the Second International Conference on Machine Learning and Cybernetics, Xi", 2-5 November 2003
- [22]. Xianmin Ma and Zhi Na "Neural network speed identification scheme for speed sensor-less DTC induction motor drive system" Power Electronics and Motion Control Conference, 2000. Proceedings. IPERC 2000. The Third International Volume 3, Issue, 2000 Page(s):1242 - 1245 vol.3.