DIRECT TORQUE CONTROL OF INDUCTION MOTOR BASED ON ARTIFICIAL NEURAL NETWORKS WITH ESTIMATE AND REGULATION SPEED USING THE MRAS AND NEURAL PI CONTROLLER

[1]MY.R.DOUIRI, [2]T.NASSER, [3]A.ESSADKI, [4]M.CHERKAOUI

[1]Student, Department of Electrical Engineering, Mohammadia School of Engineers, Rabat Morocco

[2,4]Prof. Department of Electrical Engineering, Mohammadia School of Engineers, Rabat Morocco

[3]Prof. Superior School of Technical Education, Avenue de l'armée Royale 10100, Rabat Morocco

ABSTRACT

This paper presents an improved direct torque of induction machine based on artificial neural networks. This intelligent technique was used to replace, on the one hand the conventional comparators and the selection table in order to reduce torque ripple, flux and stator current, on the other hand and the classic integral proportional (PI) in order to increase the response time period of the system, to optimize the performances of the closed loop control, and to adjust the parameters of the regulator to changes in the reference level.

Then we estimated the rotor speed using the Model Reference Adaptive Control "MRAS" method based on measurements of electrical quantities of the machine.

The validity of the proposed methods is confirmed by the simulation results.

Keywords: *Induction Motor, Direct Torque Control, Direct Torque Neural Control, Neural PI controller, Model Reference Adaptive Control (MRAS).*

1. INTRODUCTION

The robustness, the low cost, the performances and the ease of maintenance make the asynchronous motor advantageous in many industrial applications or general public. Joint progress of the power electronics and numerical electronics makes possible today to deal with the axis control with variable speed in low power applications [1]. Jointly with these technological projections, the scientific community developed various command approaches to master in real time the flux and the torque of the electric machines. One of the most recent steps in this direction is the direct torque control-DTC, which provides excellent properties of regulation without rotation speed feedback. Proposed by I Takahashi and T Noguchi and of Depenbrock, this method, appeared in second half of the eighties, competing with the methods of vectorial control. In contrast with these last, which are based on sharp but accurate mathematical formalisms, the techniques of direct torque control were originally based on qualitative and simplified knowledge of the machine behavior [1,][2],[3],[4].

Several studies are planned to decrease the harmonics on the level of the torque and flux. For that, we developed an intelligent technique to improve the dynamic performances of the direct torque control; this method consists in replacing the traditional comparators and the selection table applied to the asynchronous machine DTC by a controller based on the artificial neurons networks in order to lead the flux and the torque towards their reference values during a fixed time period [7],[8].

To ensure the asynchronous autopilotage of the machines, the electric location measure of the rotor is essential. According to the conventional methods, this information is obtained using a mechanical sensor (of position or speed) placed on the shaft. The disadvantages inherent in the use of this mechanical sensor are multiple. First, it increases the volume and the total cost of the system. Moreover, it requires a shaft end availability, which is particularly difficult for small size machines [10],[14]. The installation of this sensor requires a chock relating to the stator, operation which proves to be delicate to reproduce in series and decreases the reliability of the system. For all these reasons, it is interesting to examine the removal of the mechanical sensor and to replace it by estimators or observers of the speed and position, based on the measure of the electric quantities of the machine [13]. One of these techniques is the method of the MRAS (Model Reference Adaptive system), introduced by LANDAU, which is based on the selection of two models to represent a system. The First one is called "reference model ", the other is named "adaptive model ". The reference model should not explicitly depend on the estimated size whereas the second depends on it explicitly. An adaptive mechanism, generally PI, makes possible to approach the behavior of the adaptive model towards the behavior of the reference model [13],[14].

On the other hand, PI classical regulators for speed find some difficulties in dealing with the detuning problem. Artificial neural networks (ANN) can be used to design numerical controllers in order to maintain high dynamic performances and robustness in high and low speeds even when detuning occurs [11],[12].

In this paper we present the performance of the sensorless speed control of induction motor using a speed proportional integral (PI) neural networks controller. The artificial neural network then replaces the switching table of the conventional while the rotation speed is estimated by the MRAS method. This paper is organized as follows: The principle of classical DTC is presented in the second section, the based Artificial Neural Network is developed in the third section, the speed PI neural networks controller design is performed in the fourth section, section five presents a speed MRAS estimator and section six is devoted to illustrating by simulation the performances of this control strategy, a conclusion and reference list end the paper.

2. PRINCIPLE OF DTC

The methods of direct torque control DTC consist in controlling directly the opening or closing the inverter switches from the computed values of stator flux and torque. The state's changes of the switches are related to the evolution of the electromagnetic state of the motor. They are no longer controlled from the references of voltage and frequency given to the adjusted control of an inverter with pulse width modulation. The purpose of the switches command is to give to the vector, representing stator flux, the direction determined by the references values [2],[3].

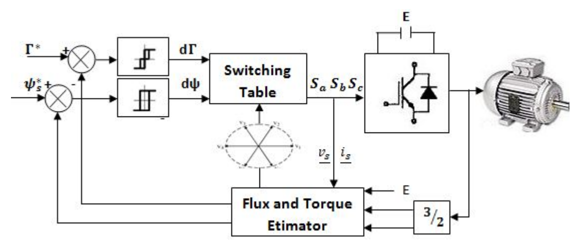

Figure 1. Basic direct torque control scheme for ac motor drives

A. Stator flux control

Stator flux estimation based on voltage model is estimated by using equation:

$$\overline{\psi}_s = \int_0^t \overline{v}_s - r_s\overline{i}_s)dt \quad (1)$$

During the switching interval, each voltage vector is constant and is then rewritten as in:

$$\overline{\psi}_s(k+1) \approx \overline{\psi}_s(k) + \overline{v}_s t_e \ (2) \text{ Or}$$

$$\Delta\overline{\psi}_s = \overline{v}_s t_e \quad (3)$$

B. Electromagnetic torque control:

The electromagnetic torque is proportional to the vectorial product between the stator and rotor flux vector:

$$\Gamma = p_p \frac{L_m}{\sigma L_s L_r} \psi_s \psi_r \sin(\widehat{\overline{\psi}_s \overline{\psi}_r}) \quad (4)$$

C. Stator flux and torque estimation

The magnitude of stator flux, which can be estimated by:

$$\begin{cases} \psi_{s\alpha} = \int_0^t (v_{s\alpha} - r_s i_{s\alpha})dt \\ \psi_{s\beta} = \int_0^t (v_{s\beta} - r_s i_{s\beta})dt \end{cases} \quad (5)$$

The stator flux linkage phasor is given by:

$$\psi_s = \sqrt{\psi_{s\alpha}^2 + \psi_{s\beta}^2} \quad (6)$$

In stationary reference frame, the machine stator voltage space vector is represented as follows [5]:

$$\bar{v}_s = v_{s\alpha} + jv_{s\beta} \quad (7)$$

$$\begin{cases} v_{s\alpha} = \sqrt{\frac{2}{3}} U_0 (S_a - \frac{1}{2}(S_b + S_c) \\ v_{s\beta} = \frac{1}{\sqrt{2}} U_0 (S_b - S_c) \end{cases} \quad (8)$$

The stator flux sector is determined by the components $\psi_{s\alpha}$ and $\psi_{s\beta}$. The angle between the referential and $\bar{\psi}_s$ is equal to:

$$\lambda = arctg \frac{\psi_{s\beta}}{\psi_{s\alpha}} \quad (9)$$

D. Electromagnetic torque estimation

Torque can be calculated using the components of the estimated flux and measured currents:

$$\Gamma = p_p (\psi_{s\alpha} i_{s\beta} - \psi_{s\beta} i_{s\alpha}) \quad (10)$$

E. Switching table

The control table is built according to the state of variables $d\psi$ and $d\Gamma$ and to the S_i zone and $\bar{\psi}_s$ position, and so, it is shaped as presented in the table 1.

Table1. Switching table for conventional direct torque control

		Sectors (S_i : i = 1 to 6)					
dψ	dΓ	S_1	S_2	S_3	S_4	S_5	S_6
1	1	V_2	V_3	V_4	V_5	V_6	V_1
	0	V_7	V_0	V_7	V_0	V_7	V_0
	-1	V_6	V_1	V_2	V_3	V_4	V_5
0	1	V_3	V_4	V_5	V_6	V_1	V_2
	0	V_0	V_7	V_0	V_7	V_0	V_7
	-1	V_5	V_6	V_1	V_2	V_3	V_4

3. ANN BASED DIRECT TORQUE CONTROL

The neurons artificial network is a model of calculation with a conception schematically inspired by the real neurones functioning system. Formal units, once assembled, help realize complex information processing. It constitutes an approach which gives more opportunities to approach the problems of perception, memory, learning and analysis under new angles. It is also a very promising alternative to avoid certain limitations of the classic numeric methods. Due to its parallel treatment of the information, it infers emergent properties able to resolve problems qualified in the past as complex [6].

In this article, a neuronal controller is used to replace hysteresis comparators and switching table, where the inputs are the error of dψ flux, of dΓ torque plus the position angle of λ statorique flux, and the output is the impulses allowing the control of the inverter switches [7],[9]. in order to generate this neuronal controller by Matlab / Simulink, we selected three linear feed-forward layers with three neurons in the input plus thirteen neurons at the hidden layer, and three neurones at the output layer, with the activation tasks respectively of type 'tansig' and 'purelin'. The structure of the direct neuronal torque control of an asynchronous machine is illustrated bellow in figure 2.

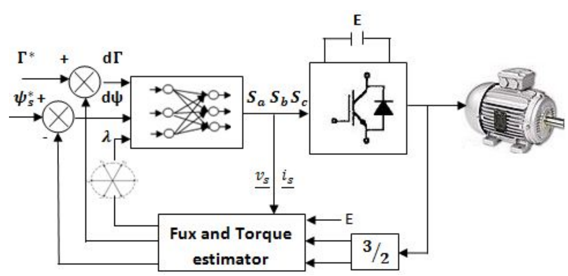

Figure 2. Direct torque neural networks controller scheme

4. PI BASED NEURAL CONTROLLER

Also, in this section, we thought of replacing the PI conventional speed regulator by a PI neuronal with the objective of increasing the response time period of the system, to optimize the performances of the closed loop control in case diverse disturbances would interfere in the regulation loop, and to adjust the parameters of the regulator to changes in the reference level [10],[12].

This regulator has two inputs; the error (which is the difference between the reference ω* and the ω output of the process) and the derived error, the output of the regulator being the control we have to apply to the entry of the process [11]. In Matlab/Simulink , we selected three linear feed-forward layers with two neurons in the input plus thirty neurons at the hidden layer and a neuron at the layer output, with the activation functions are 'tansig' for the input and the hidden layer neurons and 'purelin' for the output neuron. . The structure of PI neuronal regulator is illustrated in the Figure 3.

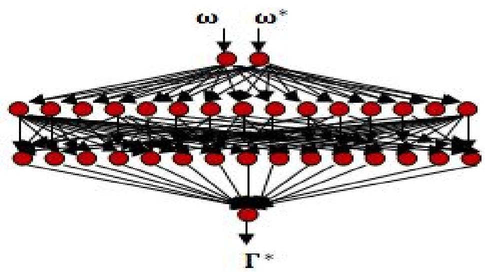

Figure 3. Neural controller structure

5. MODEL REFERENCE ADAPTIVE SYSTEM (MRAS)

The rotor speed is reconstructed using the model reference adaptive system (MRAS). The MRAS principle is based on the comparison of two estimators outputs. The first is independent of the observed variable named as model reference. The second is the adjustable one. The error between the two models feeds an adaptive mechanism to turn out the observed variable [13][14].

In this work, the actual system is considered as the model reference and the observer is used as the adjustable one.

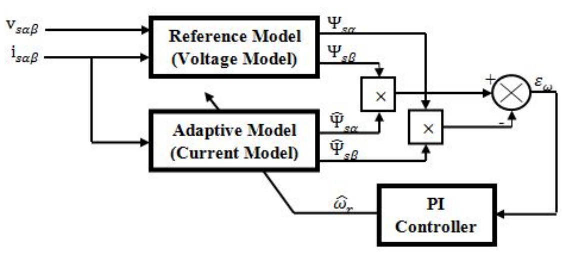

Figure 4. Conventional MRAS speed observer

A. Reference model equations

The reference rotor flux components obtained from the reference model are given by:

$$[\psi_{r\alpha\beta}]=\frac{L_r}{L_m}\left(\int([v_{s\alpha\beta}]-r_s[i_{s\alpha\beta}])dt-\sigma L_s[i_{s\alpha\beta}]\right) \quad (11)$$

B. Adaptive model equations

The rotor flux components obtained from the adaptive model are given by:

$$\left[\hat{\psi}_{r\alpha\beta}\right]=\int\left[\left(-\frac{1}{T_r}+j\omega_r\right)\left[\hat{\psi}_{s\alpha\beta}\right]+\frac{L_m}{T_r}\left[i_{s\alpha\beta}\right]\right]dt \quad (12)$$

C. Error betwen two model

Finally the adaptation scheme generates the value of the estimated speed to be used in such a way as to minimize the error between the reference and estimated fluxes. In the classical rotor flux MRAS scheme, this is performed by defining a speed tuning signal ε_{ω}, to be minimized by a PI controller which generates the estimated speed which is fed back to the adaptive model. The expressions for the speed tuning signal and the estimated speed can be given as [13],[14]:

$$\varepsilon_{\omega}=I_m(\overline{\psi}_r.\hat{\overline{\psi}}_r^{*})=(\psi_{r\beta}\hat{\psi}_{r\alpha}-\psi_{r\alpha}\hat{\psi}_{r\beta}) \quad (13)$$

$$\hat{\omega}_r=k_p\varepsilon_{\omega}+k_i\int\varepsilon_{\omega}dt \quad (14)$$

6. SIMULATION RESULTS

Induction motor parameters:

$P_n=3Kw$, $V_n=230v$, $R_s=0.85\Omega$, $R_r=0.16\Omega$, $L_s=0.16H$, $L_r=0.023H$, $J=0.105kg.m^2$, P=2, $L_m=0.058H$.

A. ANN Based DTC

The figures below represent the response of electromagnetic torque, flux, stator current and the sequences state of switch inverter. The Γ^* reference torque is a sample of [7-20-7] Nm and a flux reference $\psi_s^*=1Wb$.

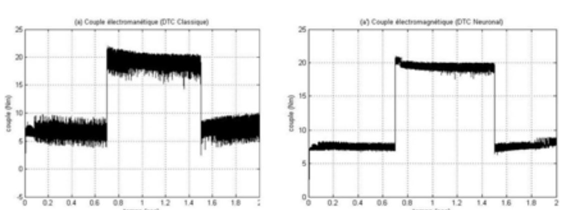

Figure 5. Comparison of the evolution of the electromagnetic torque for the traditional DTC and the neural DTC

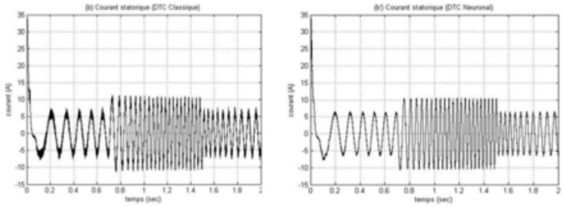

Figure 6. Comparison of the evolution of the stator current for the traditional DTC and the neural DTC

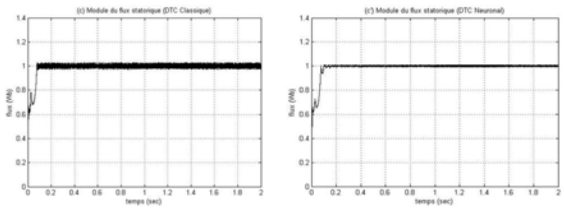

Figure 7. Comparison of the evolution of module of stator flux for the traditional DTC and the neural DTC

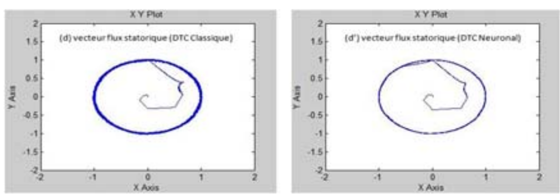

Figure 8. Comparison of the evolution of the end of the stator vector flux for the traditional DTC and the neural DTC

Figures 5,6,7,8 illustrate the performances of the classical DTC by report that obtained by neural networks.

The response torque whose is shown by the figure.5 follows exactly its reference. It is the same for the stator flux module (figure.6). The stator current (figure.7) is almost sinusoidal; its distortion is small compared with that obtained by the switching table. On (Figure 8) we observe that the flux has less distortion.

The torque ripple is reduced and its dynamic is enhanced by the new control method.

B. PI based Neural Controller

The following figures show the simulation results for PI neural corrector. A reference sample is applied respectively to t = 0.7s and t = 1.5s.

Low Speed functioning:

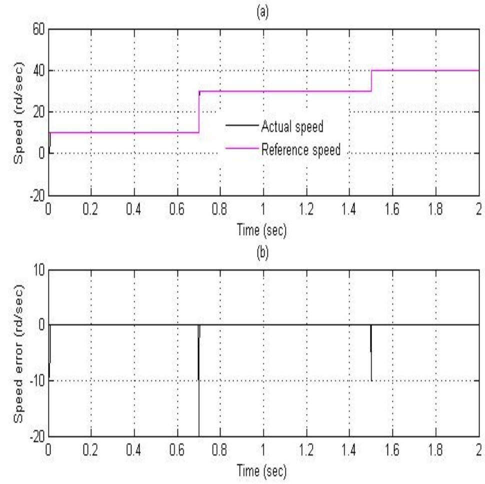

Figure 9. PI based Neural Controller Tracking Performances (Low Speed); (a) reference and actual speed, (b) speed error

High speed functioning:

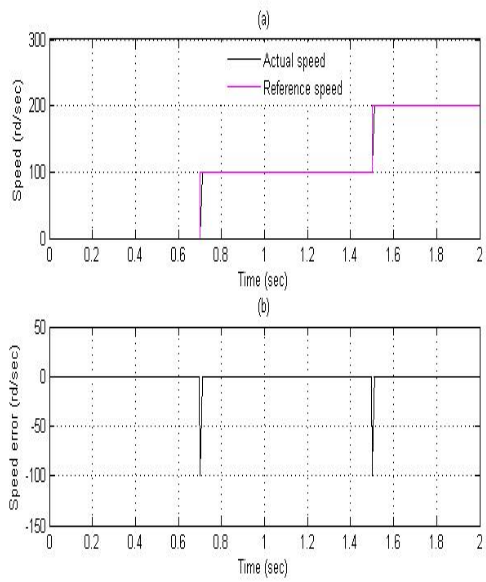

Figure 10. PI based Neural Controller Tracking Performances (High speed); (a) reference and actual speed, (b) speed error

Acceleration and speed reversal:

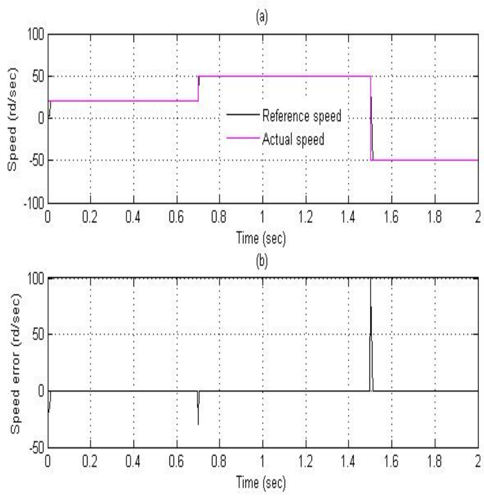

Figure 11. PI based Neural Controller Tracking Performances (Acceleration and speed reversal); (a) reference and actual speed, (b) speed error

C. Model Reference Adaptive System (MRAS)

First, acceleration of the drive is carried out in order to observe the performance of the estimator during the operation. The drive is run at various speeds by increasing it in steps to 50 rad/s, and 100 rad/s at 0.7 sec, and 1.5 sec, respectively. The speed of the motor (ω_r), estimated speed ($\hat{\omega}_r$), reference speed (ω_r^*) and speed estimation error ($\omega_r - \hat{\omega}_r$), are shown in figure 12.

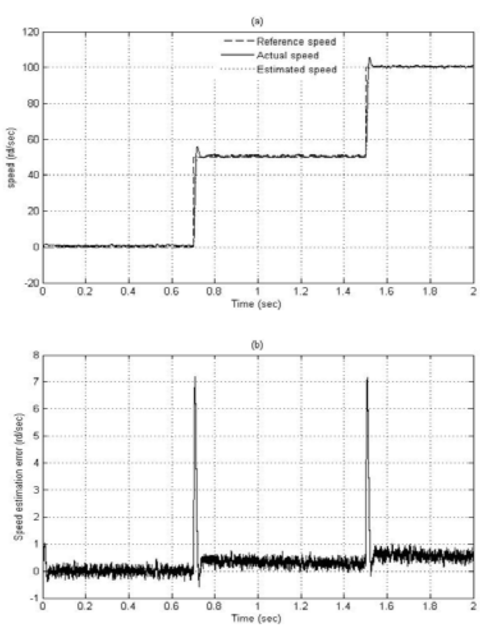

Figure 12. Operation at various speeds; (a) reference, actual and estimated speed, (b) speed estimation error

Acceleration and speed reversal is performed. A speed command of 100 rad/s at 0.7 sec is given to the drive system which was initially at rest, and then the speed is reversed at 1.5 sec (Figure 13).

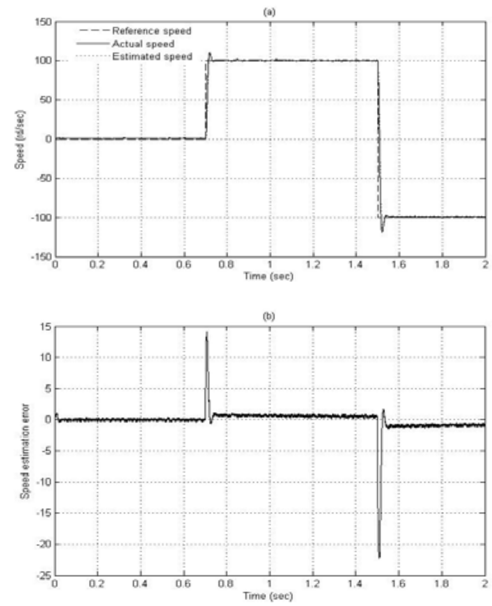

Figure 13. Acceleration and speed reversal; (a) reference, actual and estimated speed, (b) speed estimation error

7. CONCLUSION

A direct torque control of induction motor based on artificial neural networks with estimate and regulation speed using the MRAS and neural regulator PI has been described. The system was analyzed, designed and performances were studied extensively by simulation to validate the theoretical concept. The main improvements shown are:

- Limitation of the current amplitude and low distortions for current and torque;
- No flux droppings caused by sector changes circular trajectory;
- Reduction in Flux, current and torque ripples,
- Stability of system;
- Operating without speed sensor;
- Good dynamic behavior and steady state responses of speed and flux even at low and high speed.

REFRENCES:

[1] Peter Vas, ‘’Sensorless Vector and Direct Torque Control’’, University Press, London, 1998.

[2] Takahashi Isao, Noguchi Toshihiko, ‘’A New Quick-Response and High-Efficiency Control Strategy of an Induction Mîtor’’, *IEEE Transactions on Industry Applications*, Vol. IA-22, No.5, Sept/Oct 1986.

[3] M. Depenbrock, ‘’Direct Self-Control (DSC) of Inverter-Fed Induction Machine’’, *IEEE Transactions on Power Electronics*, Vol.3, No.4, Oct.1998.

[4] T. Noguchi, M. Yamamoto, S. Kondo, I. Takahashi, ‘’Enlarging Switching Frequency in Direct Torque – Controlled Inverter by Means of Dithering’’, *IEEE Transactions on Industry Applications*, Vol. 35, No. 6, Nov/Dec. 1999.

[5] Sebti Belkacem, Farid Naceri, Rachid Abdessemed, ‘’A Novel Robust Adaptive Control Algorithm and Application to DTC-SVM of AC Drives’’, *Serbian Journal of Electrical Engineering*, Vol. 7, No. 1, May 2010, 21-40.

[6] ‘’Neural Systems for Control’’, ISBN: 0125264305, Elsevier Science & Technology Books, February 1997.

[7] Luis A. Cabrera, Malik E. Elbuluk, and Donald S.Zinger, ‘’Learning Techniques to Train Neural Networks as a State Selector for Inverter-Fed Induction Machines Using Direct Torque Control’’, *IEEE-PE*, Vol. 12, No. 5, pp 788-799}, Sep, 1997,pp 788-799.

[8] Xuezhi Wu and Lipei Huang, ‘’Direct Torque Control of Three-Level Inverter Using Neural Networks as Switching Vector Selector’’, *Industry Applications Conference. Thirty-Sixth IAS Annual Meeting. Conference Record of the 2001 IEEE*, Vol.2,30 Sep-4 Oct 2001,pp 939 – 944.

[9] Y.V.Siva Reddy, M.Vijayakumar and T. Brahmananda Reddy, ‘’Direct Torque Control of Induction Motor Using Sophisticated Lookup Tables Based on Neural Networks’’, *AIML Journal*, Vol.7, Issue 1, June, 2007.

[10] G.R.A. Markadeh, J. Soltani ‘’Robust Direct Torque and Flux Control of Adjustable Speed Sensorless Induction Machine Drive based on Space Vector Modulation using a PI Predictive Controller’’, *Electrical Engineering*, Vol. 88, No. 6, Aug. 2006, pp. 485 – 496.

[11] G.MadhusudhanaRao, Dr.B.V.SankerRam, ‘’A Neural Network Based Speed Control for DC Motor’’, *International Journal of Recent Trends in Engineering*, Vol 2, No. 6, November 2009.

[12] Sung-Hoe Huh, Kyo-Beum Lee, Dong-Won Kim, Ick Choy, and Gwi-Tae Park, ‘’Sensorless Speed Control System Using a Neural Network’’, *International Journal of Control, Automation, and Systems*, vol. 3, no. 4, pp. 612-619, December 2005.

[13] Chao Yang and J. W. Finch, ‘’A Comparison of Induction Motor Speed Estimation using Conventional MRAS and AI Based MRAS with a Dynamic Reference Model’’, *Proceedings of the World Congress on Engineering*, Vol. I, 2008.

[14] H.Kraiem, M.Ben Hamed, L.Sbita and M.Naceur Abdelkrim, ‘’DTC Sensorless Induction Motor Drives based on MRAS Simultaneous Estimation of Rotor Speed and Stator Resistance’’, *International Journal of Electrical and Power Engineering* 2(5): 306-313, 2008.