DTC-ANN Control with two Level Inverter Associated by Different Observers (MRAS and KUBOTA) for Induction Machine Drives.

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***Abstract*—** In this article, we present the construction of observers of rotor flux and mechanical speed needed for robust control of the asynchronous machine. Two observers will be developed for comparison. The first is based on the techniques MRAS and the second is observer of KUBOTA, with the enhanced DTC, "sensorless DTC". The validity of the proposed methods is confirmed by the simulation results. This work is devoted to the construction of rotor flux observers and the mechanical speed necessary for the robust control of the asynchronous machine. Two speed observers will be developed for comparison. The first is based on the MRAS technique and the second is based on KUBOTA, with the improved DTC-ANN command "sensorless DTC control". The THD (Total Harmonic Distortion) of stator current, torque ripple and stator flux ripple are determined and compared with conventional DTC control scheme using Matlab/Simulink environment.

***Keywords*—** IM, Two-level DTC, Kubota observer, MRAS observer.

I. Introduction

Getting high performance with an asynchronous machine, requires complex control including requiring reliable information from process control, this information can reach the sensors, they dedicated the weakest link in the chain, so it tries to fill their functions by calculation algorithms reconstructing the machine states, such tools are the name of estimators and observer for reasons of cost or technological reasons, it is sometimes too restrictive measure some quantities of the system. However these quantities may represent important information for control or monitoring [1]. It is necessary to reconstruct the evolution of these variables that are not directly from the sensors. We must therefore carry out an indirect sensor. For this, the estimators are used or as appropriate, observers [2].

The DTC control methods of asynchronous machines appeared in the second half of the 1980s as competitive with conventional methods, based on pulse width modulation (PWM) power supply and on a splitting of flux and motor torque by magnetic field orientation, Indeed, the DTC command from external references, such as torque and flux, does not search, as in conventional commands (vector or scalar) the voltages to be applied to the machine, but search "the best "state of switching of the inverter to meet the requirements of the user [3].

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Major disadvantage of DTC is the ripple on the couple and the flux and to remedy this last problem one improves the control DTC by several techniques among these methods are modification the tables of selection, the artificial intelligences which is interested in this article and the flux is estimated by the Kubota observer.

In this work, our main objective is to exploit artificial intelligence tools namely: artificial neural networks on the DTC control and on the observer, where we use the hybrid observer of Kubota to estimate the speed and the flux and we express the estimation error then THD of stator current is evaluated.

II. DTC control

Since Depenbrock and I. Takahashi proposed DTC control of the asynchronous machine in the mid-1980s, it has become increasingly popular. The DTC command makes it possible to calculate the control quantities that are the stator flux and the electromagnetic torque from the only quantities related to the stator and this without the intervention of mechanical sensors [4].

The principle of control is to maintain the stator flux in a range. The block diagram of the DTC control is shown in Fig.1

This strategy is based generally on the use of hysteresis comparators whose role is to control the amplitudes of the stator flux and the electromagnetic torque.

$$\begin{cases} \Phi_{s\alpha} = \int_0^t (v_{s\alpha} - R_s\, i_{s\alpha})dt \\ \Phi_{s\beta} = \int_0^t (v_{s\beta} - R_s\, i_{s\beta})dt \end{cases} \tag{1}$$

$$T_e = \frac{3}{2} p \left[\Phi_{s\alpha}\, i_{s\beta} - \Phi_{s\beta}\, i_{s\alpha} \right] \tag{2}$$

(2

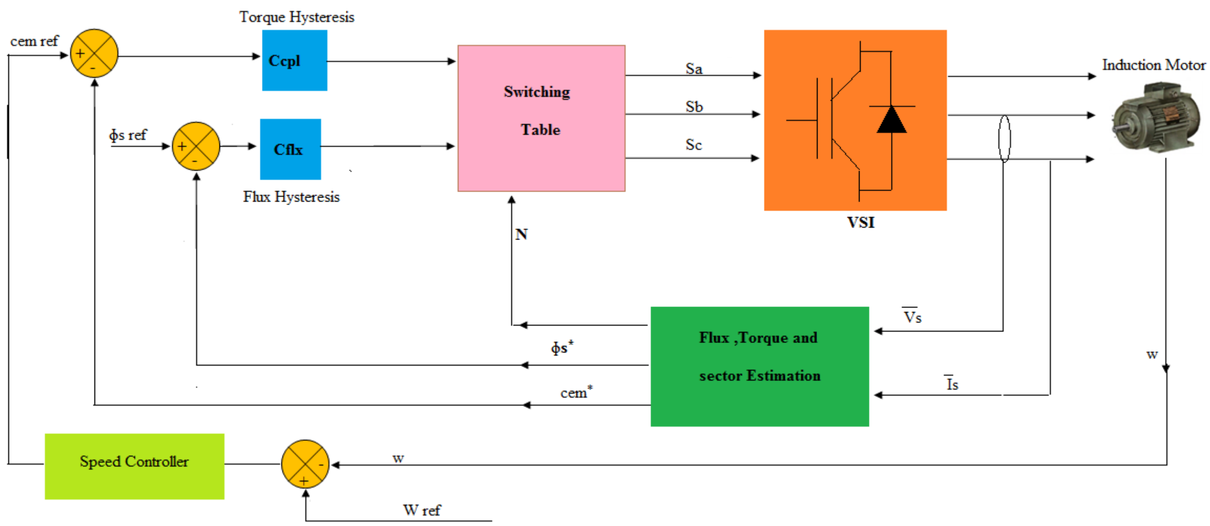


Fig. 1 Structure of classical DTC.

The DTC control method allows direct and independent electromagnetic torque and flux control, selecting an optimal switching vector. The Fig. 2 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 [5].

The switching table allows to select the appropriate inverter switching state according to the state of hysteresis comparators of flux (cflx) and torque (ccpl) and the sector where is the stator vector flux (φ_s) in the plan (α, β), in order to maintain the magnitude of stator flux and electromagnetic torque inside the hysteresis bands. The above consideration allows construction of the switching table [6].

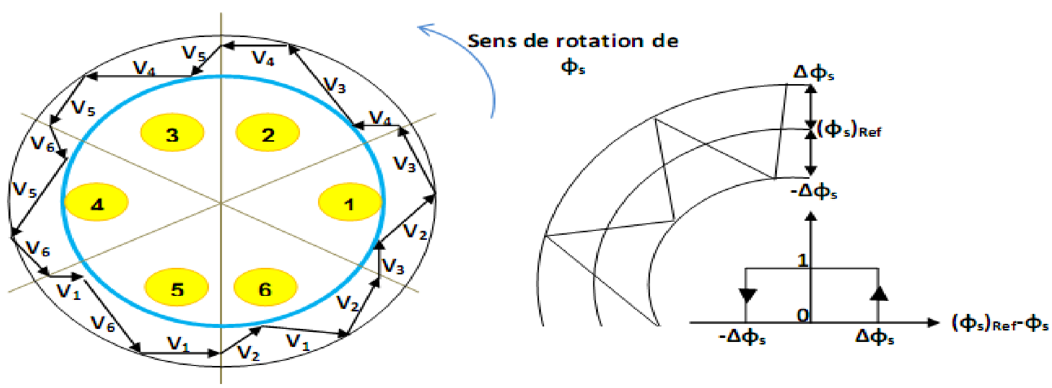


Fig. 2 Voltage vectors.

Table. I The selection of electric tension

$\Delta\varphi_s$	ΔCe	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6
0	1	V_3	V_4	V_5	V_6	V_1	V_2
	0	V_5	V_6	V_1	V_2	V_3	V_4
1	1	V_2	V_3	V_4	V_5	V_6	V_1
	0	V_6	V_1	V_2	V_3	V_4	V_5

III. DTC WITH ANN

Conventional DTC control has several disadvantages, such as obtaining a variable switching frequency, torque and flux ripples, power fluctuations, and harmonic currents in the transient and steady state, because of the use of hysteresis comparators and switching tables. For this, we proposed to study in this part the direct control of the pair based on artificial neural networks, to improve the performance of the DTC commands, where the conventional comparators and the switching table are replaced by a neural controller, so to drive the output quantities of the MAS to their reference values for a fixed period of time. Numerical simulations are presented to test the performances of the proposed methods (DTC-RNA) [7].

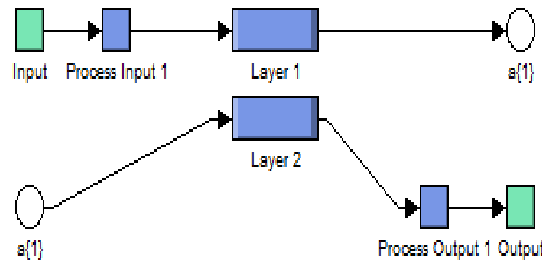


Fig.4 Structure of neural controller

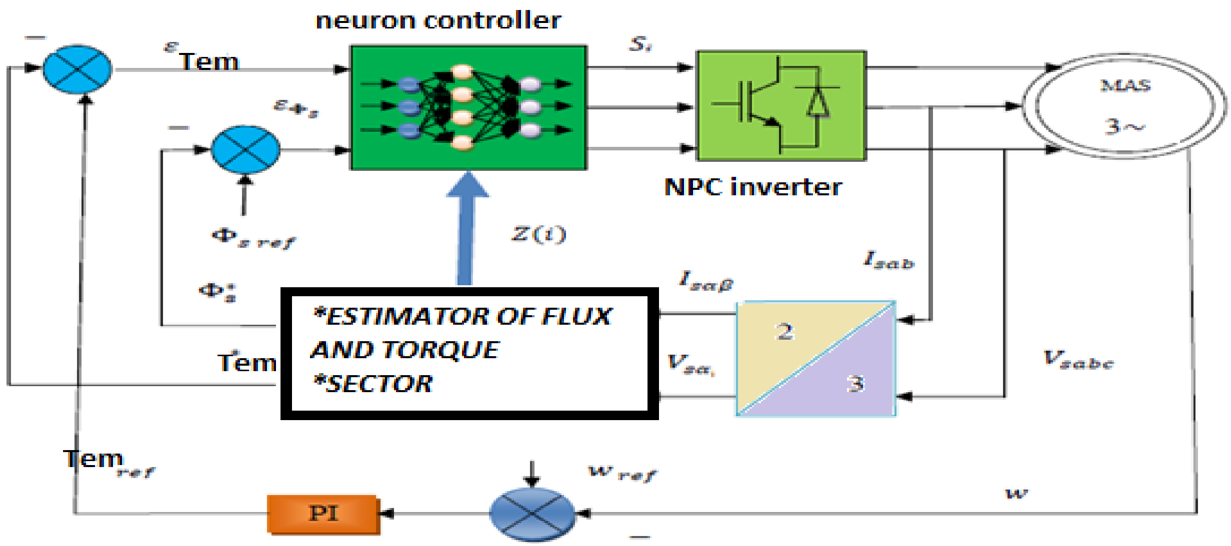


Fig. 3 DTC-RNA

The structure of the direct neural control of the torque (DTC-RNA-2N), of the asynchronous machine powered by two-level NPC inverter, is represented by fig3.

The update of the weights and Bias of this network is carried out by a retro-propagation algorithm called the Levenberg-Marquardt (LM) algorithm.

The choice of neural network architecture is based on the mean squared error (MSE) obtained during learning [8]. The following figure shows the structure of neural networks for two-level neuronal Design of Kubota observer.

IV. THE OBSERVATION

The estimators used in open loop, based on the use of a copy of a model representation of the machine. This approach led to the implementation of simple and fast algorithms, but sensitive to modeling errors and parameter variations during operation [9].
Is an estimator operating in a closed loop and having an independent system dynamics. It estimates an internal physical quantity of a given system, based only on information about the inputs and outputs of the physical system with the feedback input of the error between estimated outputs and actual outputs, using the K matrix gain to thereby adjust the dynamic convergence error [10].

The structure of the adaptive observer of KUBOTA is illustrated in Fig. 5, when the rotational speed of the machine is not measured, it is considered as an unknown parameter in the observer's system of equations based on the state model. This state model is given below [10].

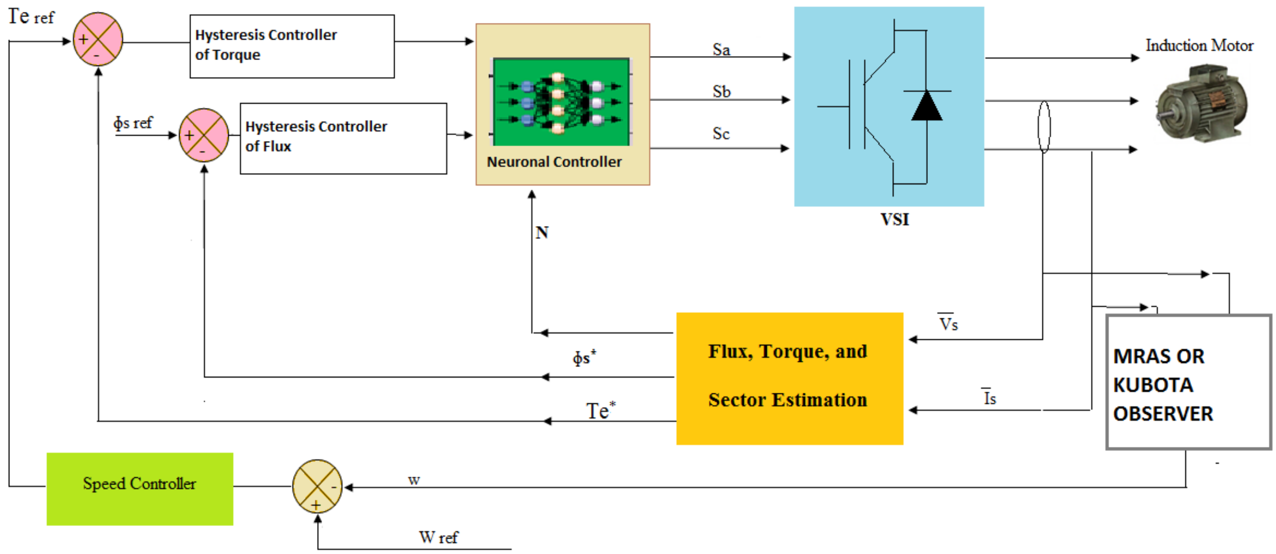


Fig.5 DTC-RNA associated by the observer

A. *Representation of the Kubota observer*:

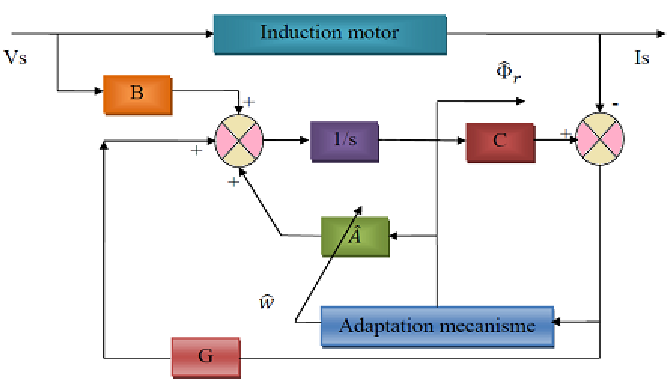


Fig.6 the observer of KUBOTA

B. *The modeling the observer KUBOTA*

- *State model*

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx \end{cases} \qquad (3)$$

With: $[A]=\begin{bmatrix} A11 & A12 \\ A21 & A22 \end{bmatrix}$ $\quad x=\begin{bmatrix} Is \\ \varphi r \end{bmatrix}$

So the observatory associated with this model is written as:

$$\frac{d\tilde{x}}{dt} = \tilde{A}\tilde{x} + B_{US} + G(I_s - \tilde{I}_s) \qquad (4)$$

With : $G = \begin{vmatrix} g_1 & g_2 & g_3 & g_4 \\ -g_2 & g_1 & -g_4 & g_3 \end{vmatrix}^T$

By asking that $e = x - \tilde{x}$ estimation error between the model and the observer.

- *Estimation error*

$$\frac{de}{dt} = (A - GC)e - \Delta A\tilde{x} \qquad (5)$$

With $;\Delta A = A - \tilde{A} = \begin{bmatrix} 0 & \Delta kwJ \\ 0 & \Delta wJ \end{bmatrix}, \Delta w = w - \tilde{w}$

- *Adaptation mechanism*

The speed adjustment mechanism is derived from the application of Lyapunov theorem on system stability. Let Lyapunov function defined positive [11]:

$$V = e^T e + \frac{(w - \tilde{w})^2}{\lambda} \qquad (6)$$

Otherwise, the derivative of this function with respect to time is negative:

$$\frac{dV}{dt} = e^T Qe - 2\Delta w\left[k(eis\alpha\,\tilde{\varphi}_{r\beta} - eis\beta\,\tilde{\varphi}_{r\alpha} - \frac{d\tilde{w}}{\lambda dt})\right] \qquad (7)$$

With: $eis\alpha = is\alpha - \tilde{i}_{s\alpha}, eis\beta = is\beta - \tilde{i}_{s\beta}$

$$Q = (A - GC)^T + (A - GC) \qquad (8)$$

Equation (8) must be set negative according to the Lyapunov stability theory. Therefore, by careful selection of the gain matrix G, the matrix Q must be a negative definite matrix and the adaptation mechanism for estimating the speed will be reduced by cancellation of the 2 nd term of the equation (9) [12].

The estimate of the speed is done by the following law :

$$\tilde{\omega} = k\lambda.\int (e_{is\alpha}\,\tilde{\varphi}_{r\beta} - eis\beta\,\tilde{\varphi}_{r\alpha})dt \qquad (9)$$

To improve the speed of dynamic observation, propose to use PI instead of a pure integrator :

$$\tilde{\omega} = k_p.(eis\alpha\,\tilde{\varphi}_{r\beta} - eis\beta\,\tilde{\varphi}_{r\alpha}) + k_i\int (e_{is\alpha}\,\tilde{\varphi}_{r\beta} - eis\beta\,\tilde{\varphi}_{r\alpha})dt \qquad (10)$$

C. *Adaptation system with reference model*

This techniques is designed on the basis of an adaptive system using two estimators flow; the first not introducing speed is called the reference model (or voltage model). The second, which is a function of speed is called adjustable model (or current model), the error produced by offset between the outputs of the two pilot estimators an adaptation algorithm that generates the estimated speed [13].

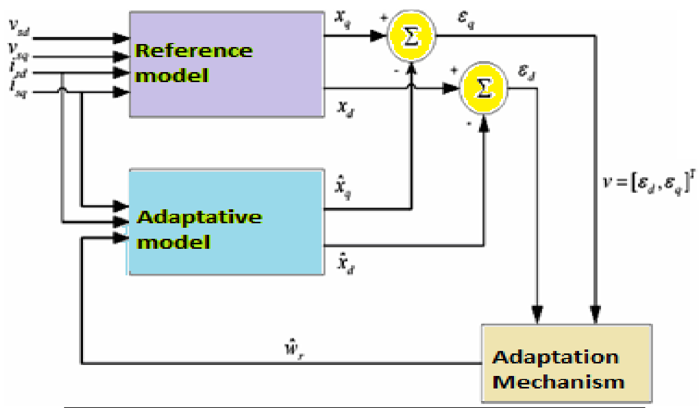


Fig.7 the MRAS technique estimation mechanism

D. *The basic model*

From stator and rotor equations of the asynchronous machine, we have:

- *Reference model*

$$\begin{cases} \dfrac{d\varphi_{r\alpha}}{dt} = \dfrac{Lr}{M}\left(V_{s\alpha} - Rs\cdot Is\alpha - \sigma\, Ls\cdot\dfrac{dIs\alpha}{dt}\right) \\ \dfrac{d\varphi_{r\beta}}{dt} = \dfrac{Lr}{M}\left(V_{s\beta} - Rs\cdot Is\beta - \sigma\, Ls\cdot\dfrac{dIs\beta}{dt}\right) \end{cases} \quad (11)$$

- *Adjustable model*

$$\begin{cases} \dfrac{d\tilde\varphi_{r\alpha}}{dt} = -\dfrac{1}{Tr}\tilde\varphi_{r\alpha} - P.\tilde\Omega.\tilde\varphi_{r\alpha} + \dfrac{M}{Tr}Is\alpha \\ \dfrac{d\tilde\varphi_{r\beta}}{dt} = -\dfrac{1}{Tr}\tilde\varphi_{r\beta} + P.\tilde\Omega + \dfrac{M}{Tr}Is\beta \end{cases} \quad (12)$$

The algorithm of adaptation is chosen so as to converge the adjustable model to the reference model thus minimizing the error and have the stability of the model. For this, the algorithm parameters are defined according to the criterion of hyper stability said Popov.

The error between the states of the two models can be expressed in matrix form by:

$$\begin{bmatrix} \varepsilon\alpha \\ \varepsilon\beta \end{bmatrix} = \begin{bmatrix} \varphi_{r\alpha} - \tilde\varphi_{r\alpha} \\ \varphi_{r\beta} - \tilde\varphi_{r\beta} \end{bmatrix} \quad (13)$$

With:

$$\frac{d}{dt}\begin{bmatrix} \varepsilon\alpha \\ \varepsilon\beta \end{bmatrix} = \begin{bmatrix} -\dfrac{1}{Tr} & -\omega \\ \omega & -\dfrac{1}{Tr} \end{bmatrix} \bullet \begin{bmatrix} \varepsilon\alpha \\ \varepsilon\beta \end{bmatrix} - \begin{bmatrix} \tilde\varphi_{r\alpha} \\ \tilde\varphi_{r\beta} \end{bmatrix} \bullet (\omega - \tilde\omega)$$

and: $$\frac{d}{dt}[\varepsilon] = [A]\bullet[\varepsilon] - [W]$$

Schauder offers an adaptation law that meets the criterion of Popov and given by the equation:

$$\tilde\omega = Q_2(\varepsilon) + \int_0^t Q_1(\varepsilon)d\tau \quad (14)$$

The criterion of Popov requires satisfaction of the following integral:

$$\int_0^t \varepsilon^T \bullet W dt \ge -\gamma^2, \gamma \succ 0 \quad (15)$$

Using equation (5), while replacing ε and w by their values, we obtain:

$$\int_0^t \left\{ \left[\varepsilon\alpha\cdot\tilde\varphi_{r\beta} - \varepsilon\beta\cdot\tilde\varphi_{r\alpha} \right] \bullet \left[\omega - Q_2(\varepsilon) - \int_0^t Q_1(\varepsilon)d\tau \right] \right\} dt \ge -\gamma^2 \quad (16)$$

The solution of equation (16) can be found using the following relation:

$$\int_0^t k \bullet \left(\frac{df(t)}{dt} \right) f(t)dt \ge -\frac{1}{2}kf(0)^2, k \ge 0 \quad (17)$$

Using the latter equation for solving Popov of the integral, the following functions are obtained:

$$\begin{cases} Q_1 = ki(\varphi_{r\beta}\cdot\tilde\varphi_{r\alpha} - \varphi_{r\alpha}\cdot\tilde\varphi_{r\beta}) \\ Q_2 = k_p(\varphi_{r\beta}\cdot\tilde\varphi_{r\alpha} - \varphi_{r\alpha}\cdot\tilde\varphi_{r\beta})\ 2) \end{cases} \quad (18)$$

By replacing this system of equations in equation (17) yields the value estimated by the following adaptation law:

$$\tilde\omega = k_p(\varphi_{r\beta}\cdot\tilde\varphi_{r\alpha} - \varphi_{r\alpha}\cdot\tilde\varphi_{r\beta}) + k_i\int_0^t(\varphi_{r\beta}\cdot\tilde\varphi_{r\alpha} - \varphi_{r\alpha}\cdot\tilde\varphi_{r\beta}) \quad (19)$$

V. RESULT OF SIMULATION

The direct torque control applied to an asynchronous machine is simulated under the Matlab/ Simulink environment. The simulation is performed under the following conditions:

The hysteresis band of the torque comparator is, in this case, fixed at ± 0.1Nm and that of the comparator of the flux at ± 0.001 wb., and reference φ_{ref} = 1 Wb,W_{ref} = 150rad/s.

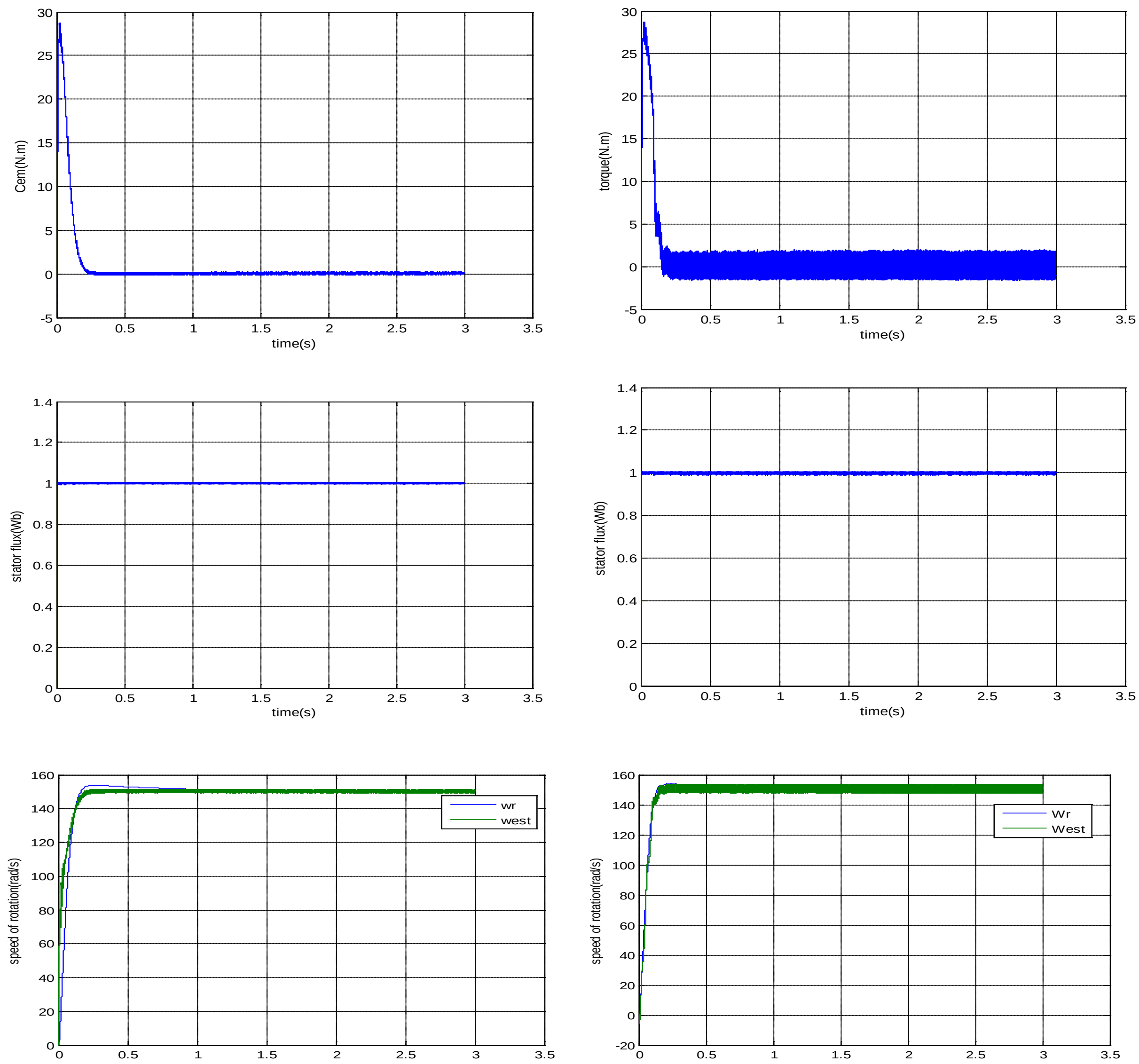
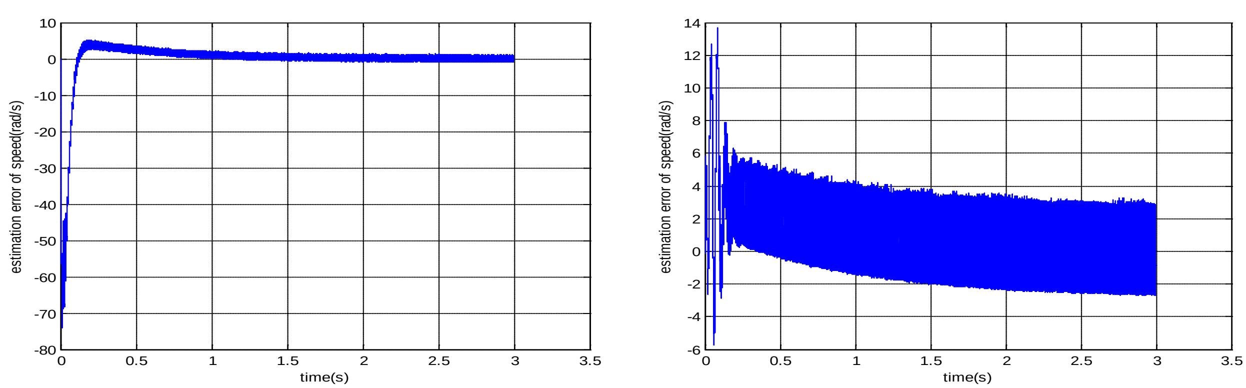


Fig.8 DTC-ANN control with MRAS observer



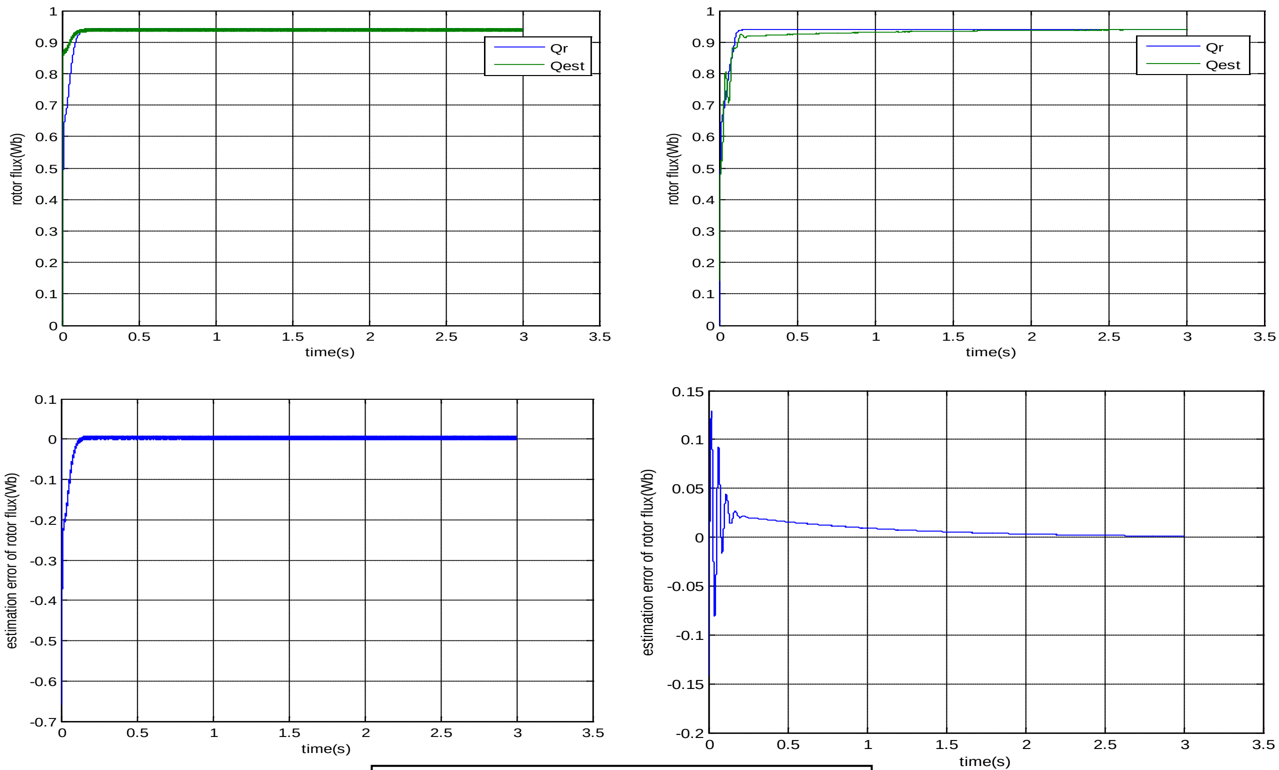


Fig.9 DTC-ANN control with KUBOTA

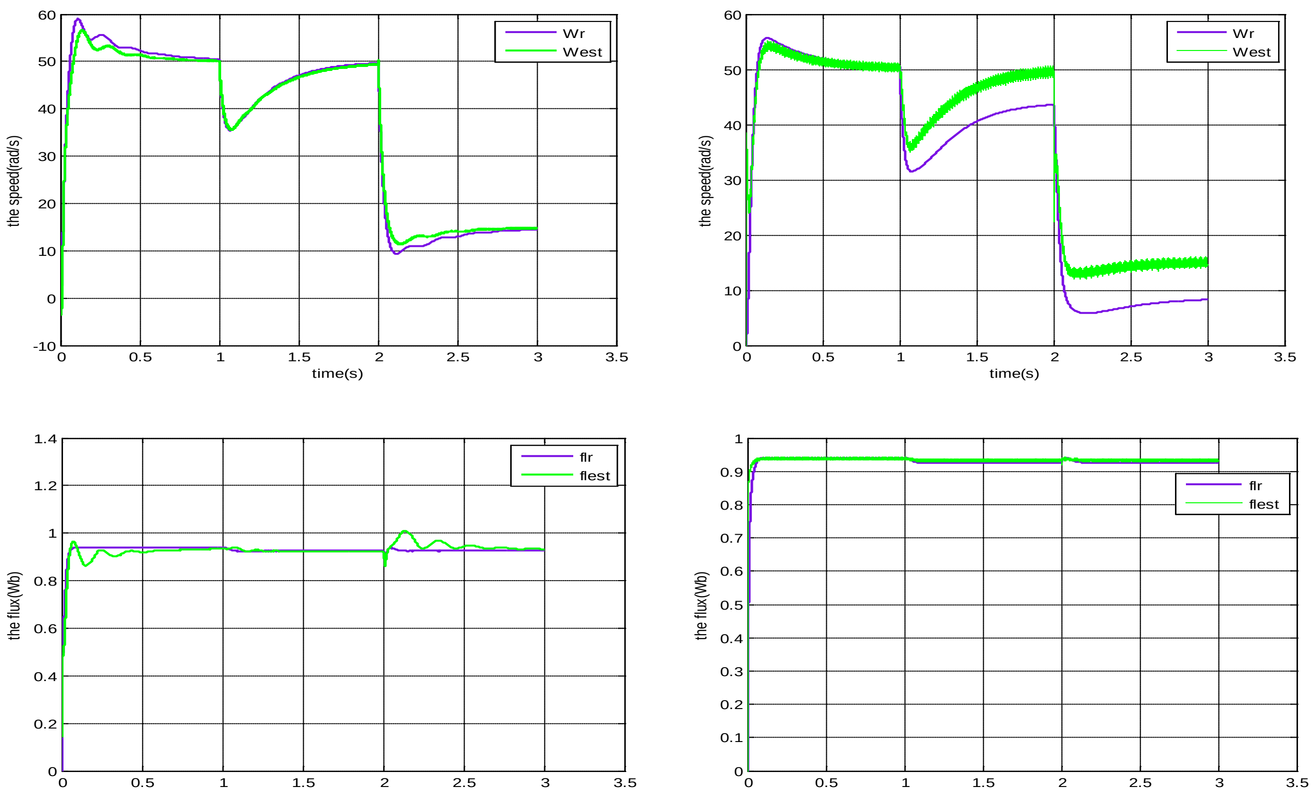


Fig10 testing the robustness of low speeds(50-15rad/s)

These results prove that our sensorless control with adaptation of is insensitive to the variations of the stator resistances. It is also noticed that the observer corrects well the rotor flux (the square of the rotor flux) and the speed of rotation, since the estimated quantities follow 'an acceptable way the actual magnitudes of the machine, hence a tracking error is almost zero between the two sizes, This implies a stable observation. But we have a problem of the ripples, especially for the observer of KUBOTA, we can say that the MRAS estimator is robust by bringing the observer of KUBOTA in this case.

Table.II comparison between the performances of KUBOTA and MRAS observer

	Precision	**swiftness**	**Oscillation**	**Low speed**
MRAS	Accurate	Fast	Existing	Good
KUBOTA	**More accurate**	**Fast below**	**Missing**	**Excellent**

This table shows that the simulation results using artificial intelligence techniques (neural hysteresis) show that the tracking of the set point is perfect. We note that the ripple of electromagnetic torque and stator flux reduces perfectly compared to conventional DTC without neural hysteresis comparator It is more apparent through the trajectory of the stator flux In addition to a large decrease in THD as shown in the table above , We were able to conclude that the DTC control by neural hysteresis showed good performance than the classical DTC control.

Simulation results show that using the observer is important in the control of the machine, the estimation error as zero in the steady state, The major advantage for KUBOTA observation technique it's insensitivity to the machine settings.

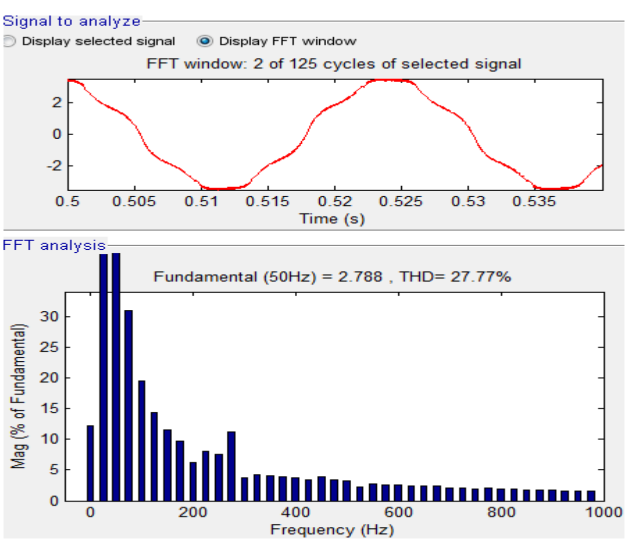


Fig.11 THD value of stator current of

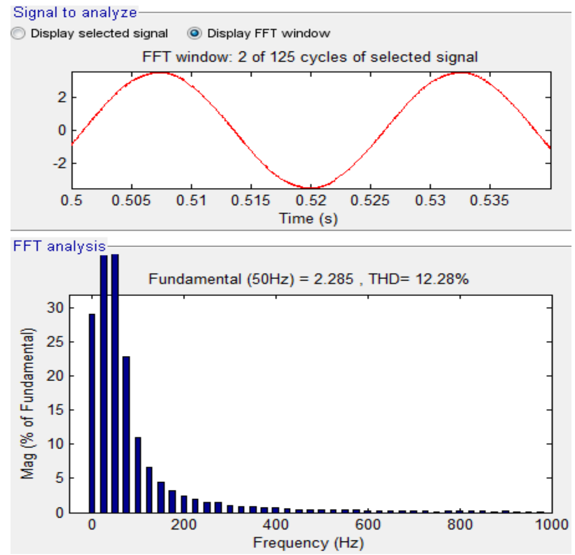


Fig.12 THD value of stator current of DTC-

Table.III comparison between the performances of classical and DTC-RNA.

	Minimizations ripples of the torque	Minimizations ripples of the flux	Ias THD (%)
DTC classic	Exist	Exist	27.77
DTC – RNA	**Few**	**Few**	**12.28**

VI. CONCLUSION

In this paper, we mainly presented the estimation of the rotor flux by the KUBOTA adaptive state observer, then we evaluated the estimation error of the flux, we also devoted to improve the performances of the direct control of the torque of the asynchronous two-level UPS powered machine based on artificial intelligence techniques by neural hysteresis, The simulation results show that the use of both estimators is important in the control of the MAS, the transient and very short regime and the error between the flows estimated and measured to zero in the steady state, the robustness tests of the estimator are also verified. According to the simulation results too, we notice that the estimation by MRAS technique performance (a little overflow, short response time, no oscillations, robust), but the observer KUBOTA also play its role, and give good result and almost similar by contribution to the 1st observer The major disadvantage of the speed estimation based on MRAS is its high sensitivity to the parameters of the machine For this, several works have proposed online adaptation techniques the stator resistance and also rotor resistance.

Finally we can say the use of the estimator brings a clear improvement to the looped structure.

VII. FEFERENCES

[1] F, Morand, « Technique d'observation sans capteurs de vitesse en vue de la commande des machines synchrone, »Thèse de doctorat, institue national des sciences appliquées Lyon France 2005.

[2] A. Ameur « Commande sans capteur de vitesse par DTC d'une machine synchrone à aimants doté d'un observateur d'ordre complet à SMC, »Thèse de magister en électrotechnique, université Batna 2003.

[3] I. Al-Rouh, «Contribution à la commande sans capteur de la MAS, » Thèse de doctorat, Univ Henri Poincaré, Nancy -1, Juillet 2004.

[4] V. Bostan, M. Cuibus, C. Ilas, G. Griva, F. Profumo, R. Bojoi, «General adaptation law for MRAS high performance sensorless induction motor drives, » PESC, Vancouver, Canada, June 17-22.

[5] H. Kubota, K. Matsuse, T. Nakano «DSP-based speed adaptive flux observer of induction motor, » IEEE Transactions on Industry.

[6] B. Sebti, «Commande par DTC d'un moteur asynchrone apport des réseaux de neurones, » Mémoire de Magister, université de Batna, 2013.

[7] D. Yacine, «Contrôle de la fréquence de commutation des hystérésis utilisés dans les commandes d'une machine à induction, » Mémoire de Magister, université de Batna, 2007.

[8] B. Elakhdar, "Commande directe du couple floue et neuronale d'un moteur synchrone à double étoile sans capteur mécanique alimenté par onduleurs Multiniveaux", Thèse doctorat en sciences, université Djillali Liabes-Sidi Bel Abbés, 2015.

[9] M.Birame,B.Mokhtari,L.Mokrani,B.Azoui,A.Naamane,N. M'sirdi , " Co-mpensateur PI flou de la variation de la résistance statorique d'un moteur à reluctance variable commande par DTC", Article ,Medimira science Publisher,volume 53,Number 4,2012.

[10] D.Yousef, "Commande directe du couple et des puissances d'une MADA associée à un systéme éolien par les techniques de l'intelligence artificielle", These Doctroat en science,université Djillali liabes de Sidi-Bel-Abbes, 2015

[11] A.Hammoumi,A.Massoum,A.Meroufel,P.Wira, "Appli cation des Réseaux de Neurones pour la commande de la machine Asynchrone sans capteur mécanique", Article ,Medimira science Publisher,volume 53,Number 2,2012.

[12] L.Youb,A.Cracunescu, "Etude Comparative entre la commande vectorielle a flux oriente et la commande directe du couple de la machine asynchrone", U.P.B.SCI.Bull,series C,Vol.69,NO.2,2007.

[13] Kubota, H.; Matsuse, K., "Speed sensorless field oriented control of induction motor with Rotor resistance adaptation", Proceeding of IEEE-IAS 1993 Annual Meeting, vol. 1, pp. 414 – 418, Toronto, Canada, 2 - 8 Oct. 1993.