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Two-level DTC control based on neural hysteresis comparators with sensorless induction machine drives using kubota observer

Ahmed DRIS[*1], Habib BENBOUHENNI[1], Mokhtar BENDJEBBAR[2]
[1]Ecole Nationale Polytechnique d'Oran Maurice Audin, Oran Algeria
[2]Université de Science Et Technologie (USTO), Oran, Algeria.

Abstract: Direct torque control (DTC) is an advanced and simple control method for induction motor (IM) drives has many advantages over other variable frequency control methods, but it has a common disadvantage of high torque ripple and stator flux ripple. In this paper, DTC is applied for two-level inverter fed IM drives based on neural hysteresis comparators and the estimated the rotor speed using the Kubota observer method based on measurements of electrical quantities of the motor. The validity of the proposed methods is confirmed by the simulation results. 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, Neural hysteresis, THD.

1. 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].

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.

[*] Corresponding author.
E-mail: drisahmed82@yahoo.com (A. DRIS).
Address: BP: 139, Chorfa, Chlef, Algeria.

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

2. 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.

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

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

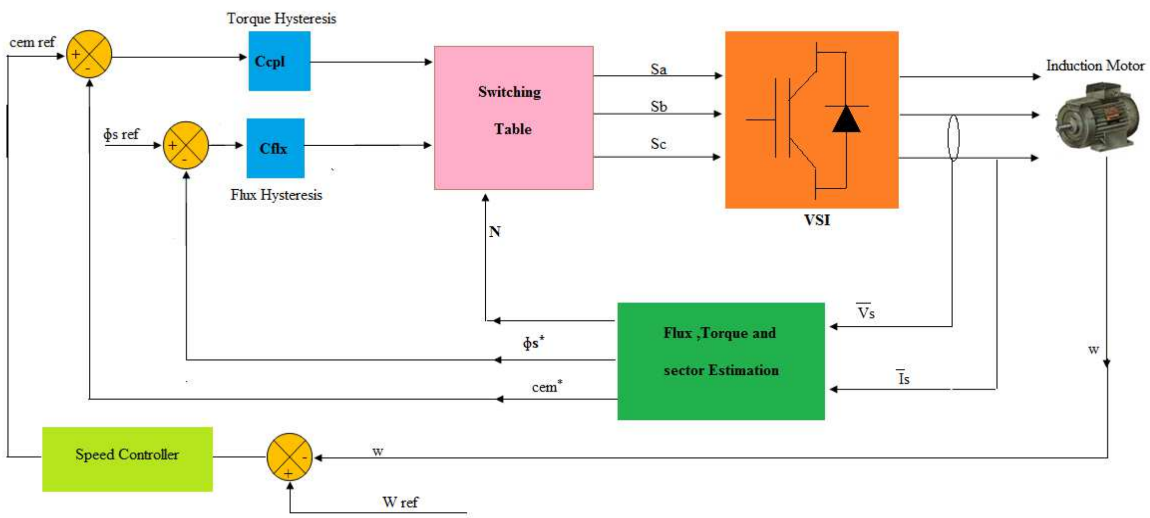


Fig. 1 Structure of classical DTC.

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 [4, 5].

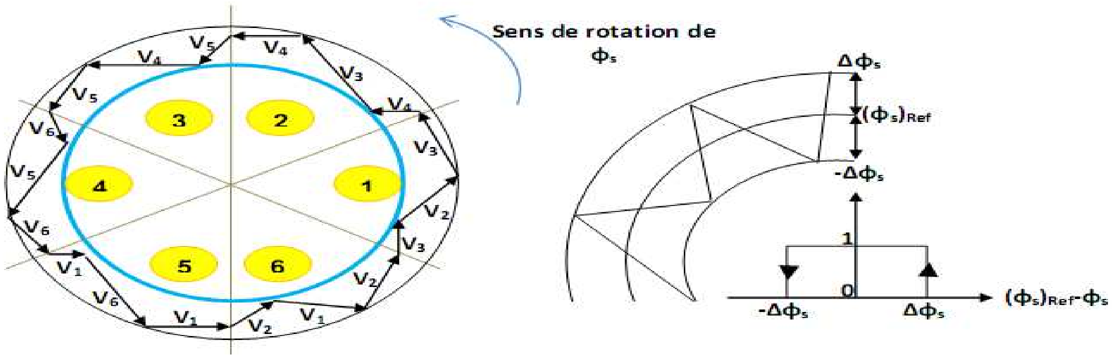


Fig. 2 Voltage vectors.

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 [5].

Table.1
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

3. DTC with neural hysteresis comparators and kubota observer

The principle of neural networks DTC with kubota observer is similar to traditional DTC control. The difference is using a neural networks controller to replace the torque and flux hysteresis loop controller, and using kubota observer for observing speed of induction motor. As shown in Fig. 3.

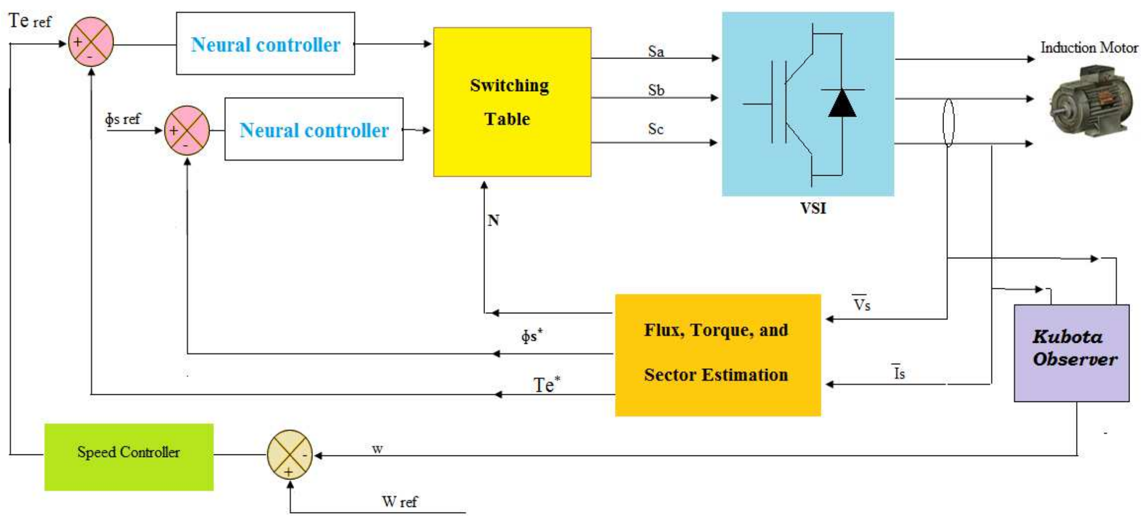


Fig. 3 Structure of the DTC control sensorless with neural hysteresis and kubota observer.

3.1 Design of neural hysteresis comparators

Neural networks are mathematical models inspired by the brain's functioning of the human being. Their faculty of learning, generalization and approximation, make two new solutions for the modeling, identification and control of processes by their ability to process input-output data of the system [7]. The choice of a neural network to improve the performance of the proposed DTC control is obtained after several simulation tests.

The hysteresis comparators is replaced by a perceptron neuron network, comprising a 1 neuron input layer, a four neuron hidden layer, and a 1 neuron output layer. The activation functions are of tansig forms for the input layer and purelin for the hidden layer neuron, and trainlm for the output layer neuron. Fig. 4 illustrates the architecture of the neural hysteresis comparator of torque and flux hysteresis.

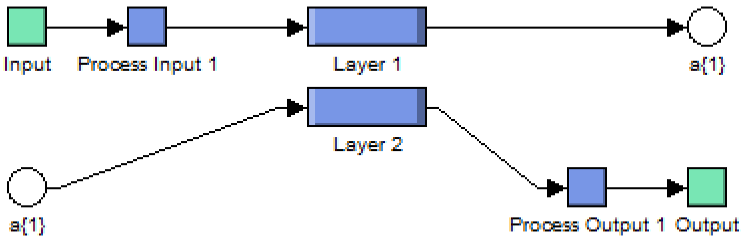


Fig. 4 Architecture of the neural hysteresis controller of torque and flux.

3.2 Design of the kubota observatory

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.

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 [6, 7].

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 [5, 6, 7].

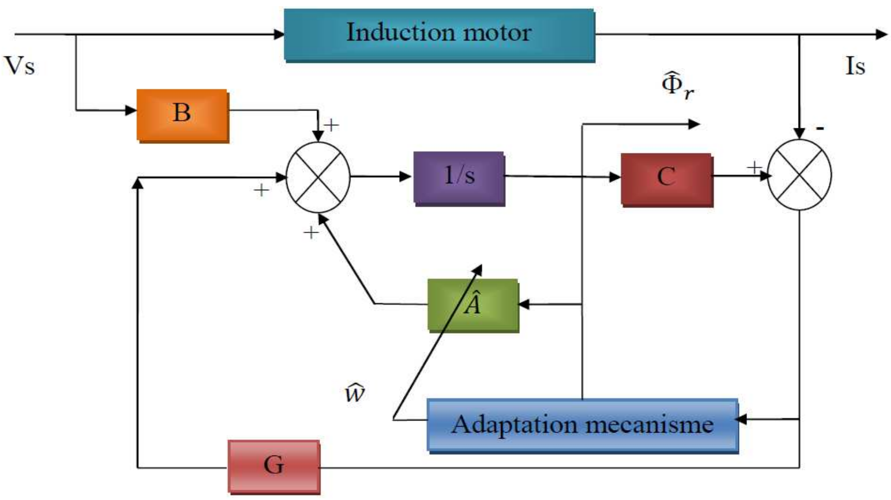


Fig. 5 Structure of the adaptive Kubota observer.

The modeling the observer KUBOTA

- **State model**

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx \end{cases} \qquad [A]=\begin{bmatrix} A11 & A12 \\ A21 & A22 \end{bmatrix} \qquad x=\begin{bmatrix} Is \\ \varphi r \end{bmatrix} \tag{3}$$

So the observatory associated with this model is written as:

$$\frac{d\tilde{x}}{dt}=\tilde{A}\tilde{x}+B_{us}+G(I_s-\tilde{I}_s) \qquad G=\begin{vmatrix} g_1 & g_2 & g_3 & g_4 \\ -g_2 & g_1 & -g_4 & g_3 \end{vmatrix}^T \tag{4}$$

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

- **Estimation error**

$$\frac{de}{dt}=(A-GC)e-\Delta A\tilde{x} \;;\Delta A = A-\tilde{A} = \begin{bmatrix} 0 & \Delta kwJ \\ 0 & \Delta wJ \end{bmatrix}, \Delta w = w-\tilde{w} \tag{5}$$

- **Adaptation mechanism**

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

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

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

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

With:

$$eis\alpha = is\alpha - \tilde{i}s\alpha, eis\beta = is\beta - \tilde{i}s\beta$$
$$Q = (A-GC)^T + (A-GC) \tag{8}$$

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).

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

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

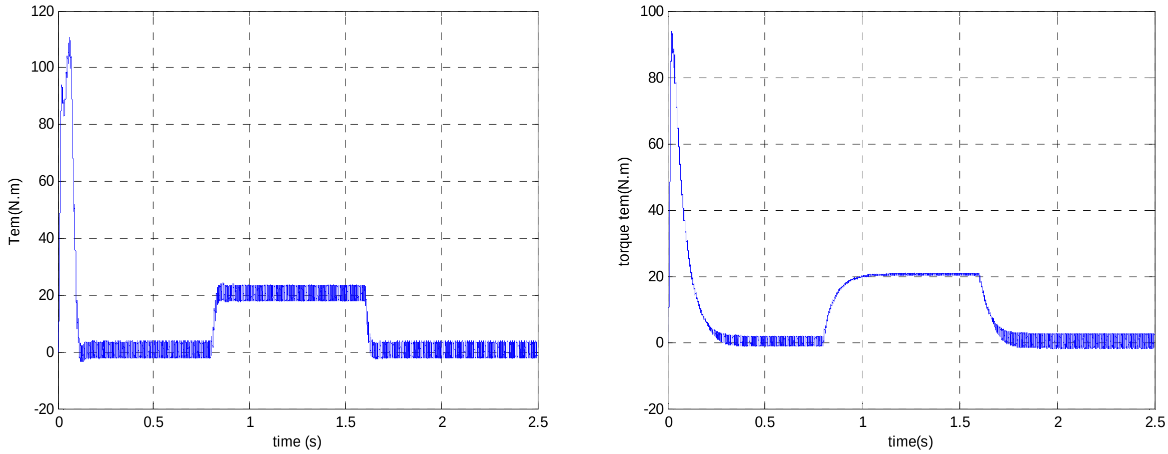
To improve the speed of dynamic observation, propose to use PI instead of a pure integrator:

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

4. Simulation results

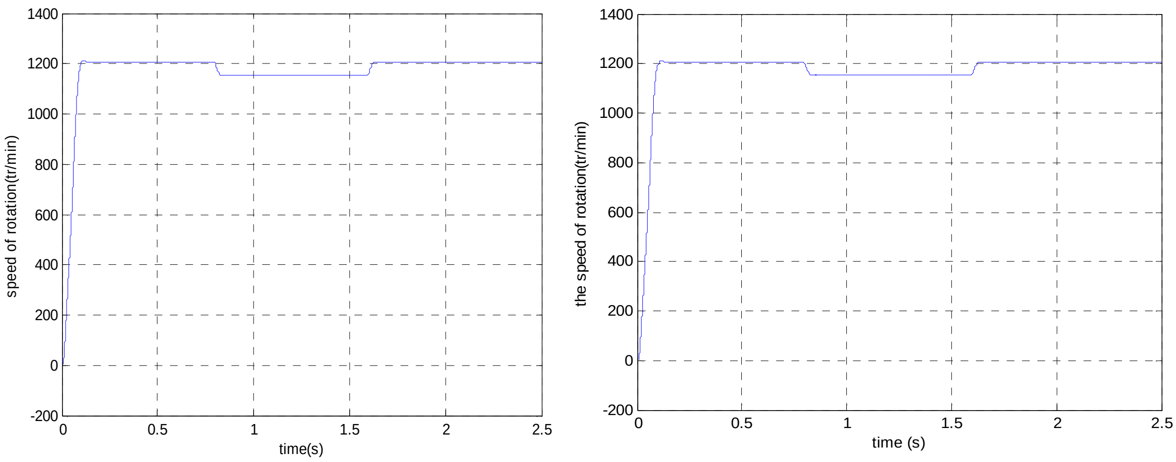
The direct torque control applied to an asynchronous machine is simulated under the Matlab/ Simulink environment. The simulation is performed under the following conditions:

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} = 2.4 Wb, Where on the right side neural DTC with kubota observer and the left side classical DTC.



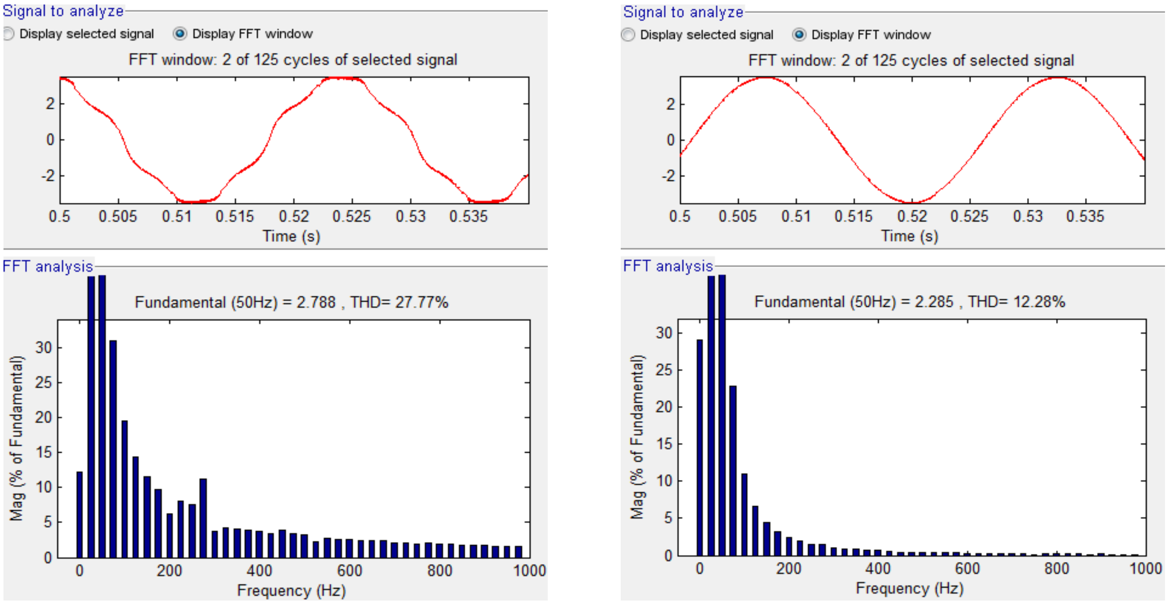
a)Classical DTC control b)DTC with neural hysteresis and kubota observer

Fig. 6 Torque responses



a)Classical DTC control b)DTC with neural hysteresis and kubota observer

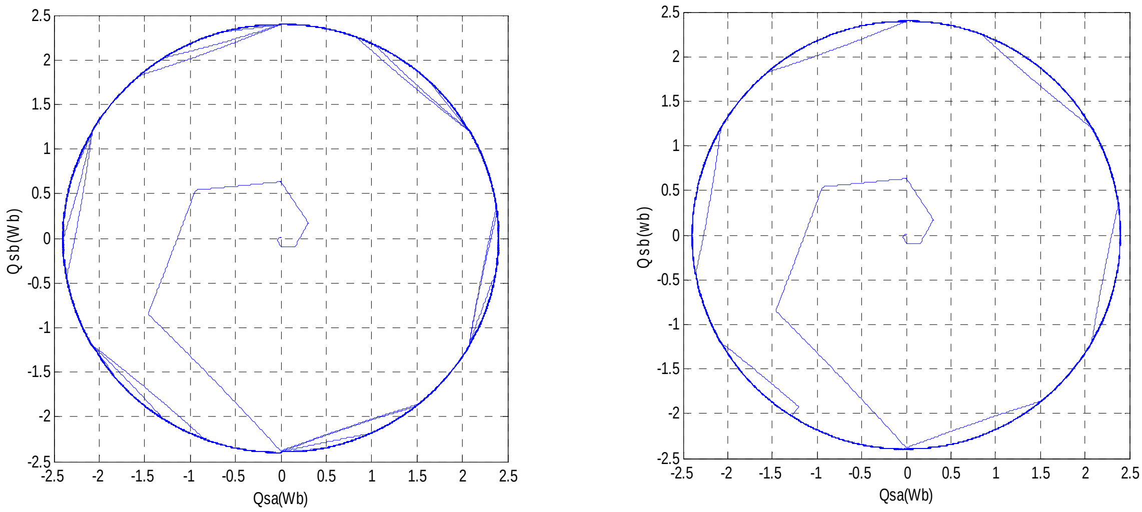
Fig. 7 Speed responses



a)Classical DTC control

b)DTC with neural hysteresis and kubota observer

Fig. 8 THD value of stator current



a)Classical DTC control

b)DTC with neural hysteresis and kubota observer

Fig. 9 Trajectory of the stator flux

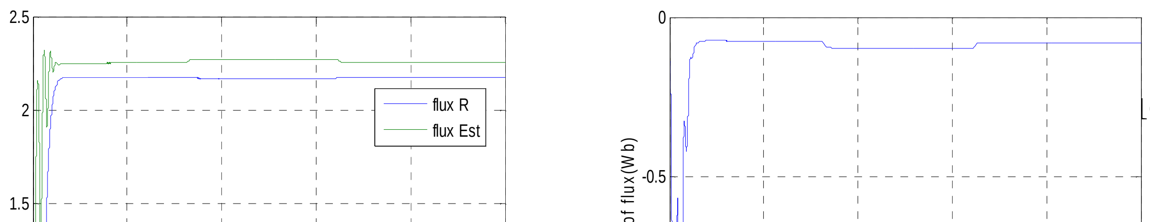


Fig. 10 Estimation the flux by Kubota observer.

Table. 2
Comparative study between classical DTC and DTC with neural hysteresis and kubota observer

	Minimizations ripples of the torque	**Minimizations ripples of the flux**	**Ias THD (%)**
Classical DTC	Exist	Exist	27.77
DTC with neural hysteresis and kubota observer	**Few**	**Few**	**12.28**

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.

5. 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. In order to improve the performance of the DTC (torque ripple reductions, flux, and the THD value of the stator current), simulation tests of the control by variation and inversely of the load torque, were presented. , the results obtained show that this strategy proposed with the techniques of the artificial intelligence is very powerful.

6. References

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