

Improvement of sensor less induction motor dynamic behaviour by ANN controller

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ABSTRACT: This thesis is the output of research work which contributes to the technologic innovation that industrial world will live. High elevations of sensorless asynchronous motor characteristic values still give big problems in control engineering. In order to achieve the objectives, some of fundamental notion of artificial neural network were given. The multivariable control was applied to a three phase asynchronous motor using PI controller. The PI conventional controller was identified by artificial neural networks to get an absolute neural controller. Regarding to some weakness of conventional controller, neural controller system improvement was elaborated by combining the conventional controller with neural controller and good results were acquired in MATLAB Simulink environment.

Keywords: Multivariable control, artificial neural networks, nonlinear system, asynchronous motor, vectorial control.

I- INTRODUCTION

Controlling the linear system is easy to master, either on theory or on practice. But controlling the nonlinear systems is not easy enough. The world that surrounds us describes non linearity aspect in structure and in shape. This non linearity needs to be controlled especially in industry field. The squirrel asynchronous motor is nonlinear system which presents high non linearity and varying parameters during operation. These varying parameters could compromise the system stability.

The neural controller is one of the technics which could manage to ensure better performance for the nonlinear system as asynchronous motor. It has the smart capacities as:

- The computing rapidity on real time.
- Insurance of data supplying in case of system internal irregularity.
- Efficiency when working with noise.

Several searchers were trying to explore the advantages of neural networks for dynamic system control and especially in robotic [1][2] and for asynchronous motor control field [3] [4]. We can see more details about the control structures with neural model in [5][6].

This work exposes one proposed neural controller system that is applied to brushless asynchronous motor and compared with conventional controller such PI. Artificial neural network theory is explored such as activation function, structure, identification and learning. Mathematic model of the asynchronous motor is given. Then, more details on field oriented neural controller are developed. Simulations are worked out using MATLAB Simulink environment in order to observe the motor behavior on different operating mode.

II- FUNDAMENTAL OF ARTIFICIAL NEURAL NETWORK

One of the most attractive works of artificial neural network (ANN) is their capacity to learn and achieve better approximation using training data [1]. A neural network can be expressed by a mathematical model that executes processing characteristics similar to biological neural networks, formed of numerous nonlinear computational elements (neurons), operating in parallel and connected to each other by forces which are expressed by numerical values called weight [8].

The basic element of an ANN is the neuron which has a summer and an activation function as shown in figure 1. The mathematical model of a neuron is given by:

$$y = \varphi\left(\sum_{i=1}^N w_i * x_i + b\right) \quad (1)$$

Where $(x_1, x_2 \dots x_N)$ are the input signals of the neuron, $(w_1, w_2, \dots w_N)$ are their corresponding weights and b a bias parameter. φ is a tangent sigmoid function and y is the output signal of the neuron.

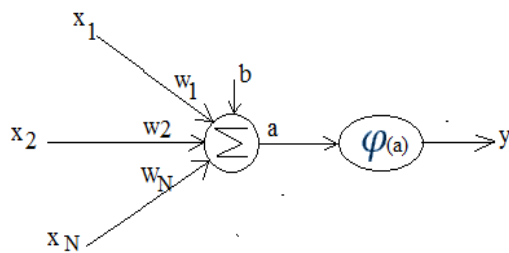


Figure 1: Artificial neural network

In this work, multilayer perceptron is used for elaborating the proposed controller. It is made up of three types of layers, an input layer, hidden layers, and output layer.

III-LEARNING ALGORITHMS

The most popular supervised learning algorithm is back propagation [1], which is a branch of machine learning concerned with inferring models from a set of known pairs of inputs and outputs. The algorithm used for determination of optimal number of neurons in the hidden layer starts with construction of the neural network with at least $N/2$ hidden neurons, where N is the number of input variable. Applying the algorithm for back propagation of the error consists of a forward and backward action. In the forward phase, it computes a mean square error.

$$E(k) = \frac{1}{N} \sum_{i=1}^N (d_i(k) - y_i(k))^2 \quad (2)$$

Where d_i is the desired response, y_i is the actual output, k is the iteration number of input-output data. The weights are reset so that the error of the network to be minimized. The weights associated with the output layer of the network are therefore updated using the following formula [7]:

$$w_{ji}(k + 1) = w_{ji}(k) - \eta \frac{\partial E(k)}{\partial w_{ji}(k)} \quad (3)$$

Where w_{ji} is the weight connecting the j th neuron of the output layer to the i th neuron of the previous layer, η is the constant learning rate [7].

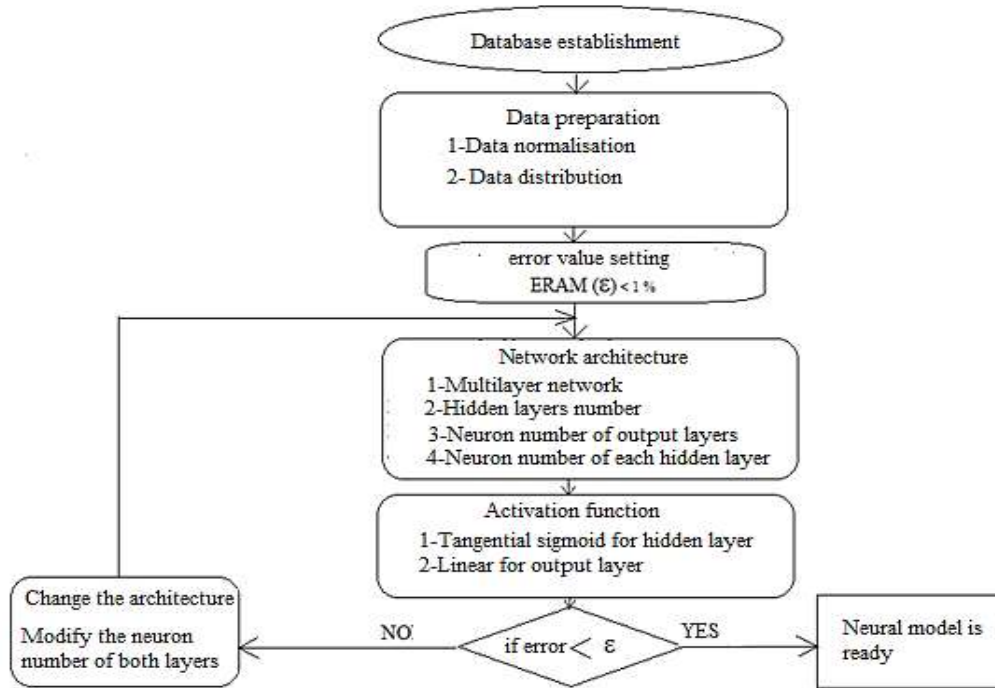


Figure 2: Organization of ANN conception.

IV- STATE SPACE MODEL OF INDUCTION MOTOR

Modeling process is an indispensable step before controlling one. Some hypotheses are to be considered. Park transformation is needed to fulfill the three to two axis transformations that is served in the computing task of control. The linearized

$$\frac{d}{dt} \begin{bmatrix} i_{ds} \\ i_{qs} \\ \varphi_{dr} \\ \varphi_{qr} \end{bmatrix} = \begin{bmatrix} -\frac{1}{\sigma\tau_s} - \frac{1-\sigma}{\sigma\tau_r} & \frac{d\theta_s}{dt} & \frac{1-\sigma}{\sigma\tau_r M} \\ -\frac{d\theta_s}{dt} & -\frac{1}{\sigma\tau_s} - \frac{1-\sigma}{\sigma\tau_r} & -\frac{1-\sigma}{\sigma M} \left(\frac{d\theta_s}{dt} - \frac{d\theta}{dt} \right) \\ \frac{M}{\tau_r} & 0 & -\frac{1}{\tau_r} \\ 0 & \frac{M}{\tau_r} & -\frac{d\theta}{dt} \end{bmatrix} \begin{bmatrix} i_{ds} \\ i_{qs} \\ \varphi_{dr} \\ \varphi_{qr} \end{bmatrix} + \frac{1}{\sigma L_s} \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_{ds} \\ V_{qs} \end{bmatrix} \quad (4)$$

The control consists of keeping the rotor flux q-axis at zero in order to fulfill the orientation condition. Since the magnet flux is constant, thus the electromagnetic torque is linearly proportional to the q-axis current which is defined by the machine operating mode (with load or without load). The electromagnetic torque is obtained from the speed controller output. The rotor speed control is performed by closed loop control. As a result, accurate reference tracking and maximum torque can be gained in addition to high dynamic performance.

The electromagnetic torque equation is given by:

model of asynchronous machine can be presented in state space form. The asynchronous machine is fed by voltage source. The dynamic model state space for the asynchronous machine in d-q transformed field reference frame is depicted as follow:

$$C_{em} = \frac{3}{2} MP (I_{qs} I_{dr} - I_{ds} I_{qr}) \quad (5)$$

We take the flux equation to deduce the rotor current:

$$I_{dr} = \frac{\varphi_{dr} - M I_{ds}}{L_r} \quad (6)$$

$$I_{qr} = \frac{\varphi_{qr} - M I_{qs}}{L_r} \quad (7)$$

The electromagnetic torque becomes:

$$C_{em} = \frac{3}{2} P \frac{M}{L_r} (\varphi_{dr} I_{qs} - \varphi_{qr} I_{ds}) \quad (8)$$

and assuming that:

$$\varphi_{rd} = \varphi_r \text{ et } \varphi_{rq} = 0 \quad (9)$$

We finally have:

$$C_{em} = \frac{3}{2} P \frac{M}{L_r} (\varphi_r \wedge I_{qs}) \quad (10)$$

V- SPEED CONTROLLER

The control objective is to satisfy the required performance criteria. We can specify them as follows:

- Accuracy in tracking.
- Accuracy in regulation: rise time; response time; overshoot; stability.
- Robustness through disturbance
- Sensibility of parameters variation.

The PI conventional controller is used and defined by:

$$G(s) = k_p + \frac{k_i}{s} \quad (11)$$

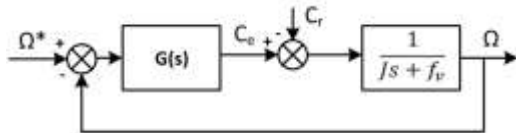


Figure 3: Speed regulation diagram.

VI- STATOR CURRENT CONTROLLER

The controller is composed of two main parts:

- The comparator which receives reference information and measured parameter that issues the difference ε or error.
- The controller which function is to eliminate this error.

The PI conventional controller is used and we have the following diagram:

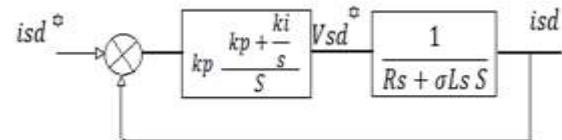


Figure 4: Stator regulation diagram.

After the closed loop transfer function we finally get:

$$\begin{cases} k_{ii} = 2\rho^2\sigma L_s \\ k_{pi} = 2\rho\sigma L_s - R_s \end{cases} \quad (12)$$

The two stator current controllers are similar.

VII- FIELD ORIENTED NEURAL CONTROL TOPOLOGY

The proposed field oriented neural control topology is displayed on figure 5. The conventional controller PI is replaced by the trained neural networks. The neural networks learn to approximate the conventional controller PI function. To choose the best candidate of the neural model that generates the minimum error. The following table gives the details of the training result.

Tableau 1: ANN parameters

ANN	PIcontroller	flux block
Input number	1	2
Output number	1	2
Hidden layer number	1	1
Neuron in hiddenlayer	11	5
Learning algorithm	Levenberg-Marquardt	Levenberg-Marquardt

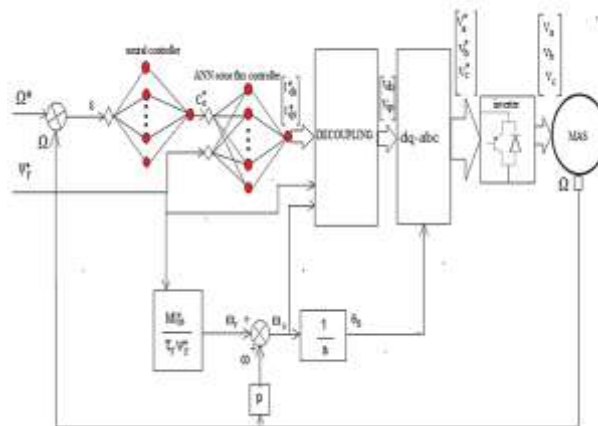


Figure 5: Neural field oriented vectorial controller without stator current controller.

The figure 5 diagram is used for the static phase of the operating function.

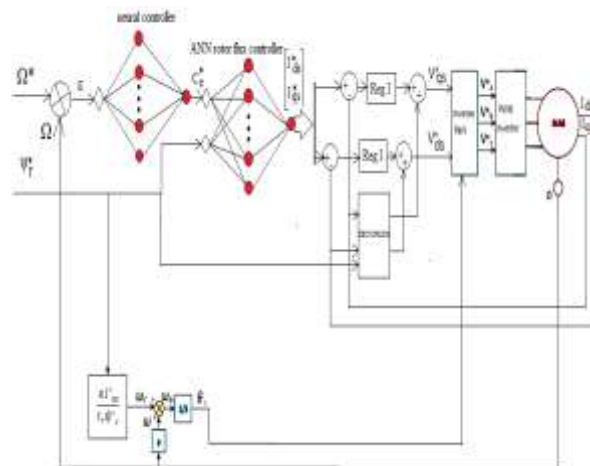


Figure 6: Neural field oriented vectorial controller with stator current controller.

The figure 6 Diagram is used for the dynamic operating phase.

VIII- RESULTS AND DISCUSSION

1- STATIC PHASE

a) Variable speed operating mode

- Results

The motor speed is varied at different values less than the nominal speed [314 – 200 – 50] rad/s.

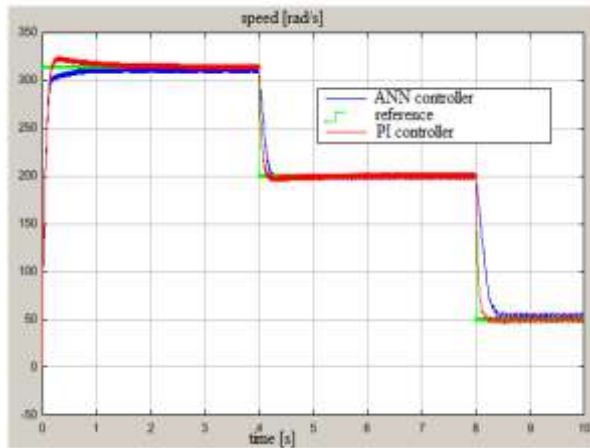


Figure 7: Variation of rotor speed.

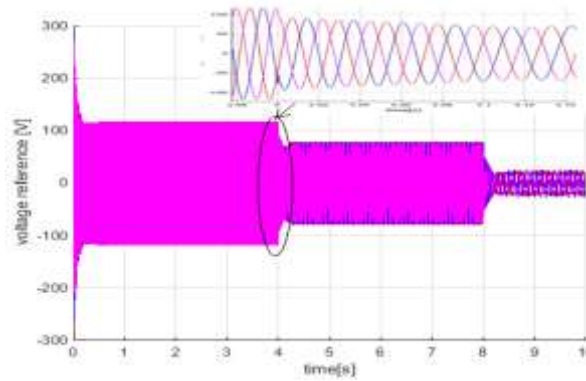


Figure 8: Inverter reference voltage

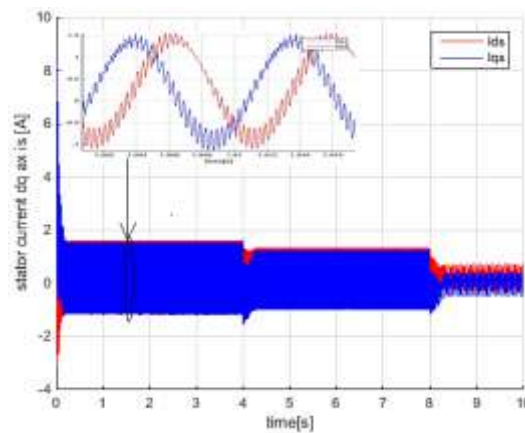


Figure 9: Stator current in dq axis.

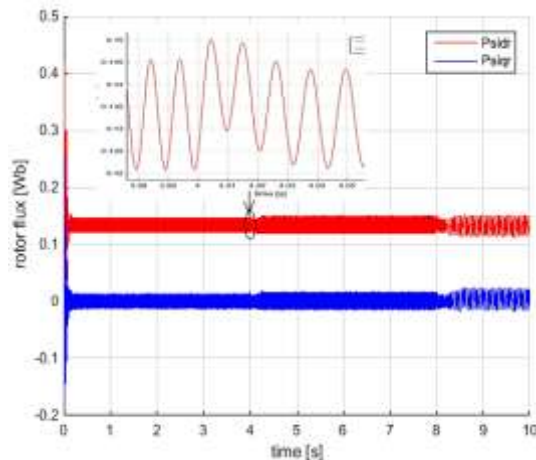


Figure 10: Rotor flux in dq axis.

Discussion

In order to taste the performance of the controller on the speed variation, the asynchronous motor is fed by a two-level voltage inverter which reference voltage evolution is displaying on the figure 8. When the speed is varied from 314 through 200 to 50 rad/s, the motor speed response on figure 7 explains the capacity of the controller of tracking the reference speed with rapidity and without overshoot. It's denoted on the figures 8 and 9 that when the motor operates under its nominal speed, the reference voltage and the stator current

decrease proportionally with the rotor speed. The sudden change of the reference speed generates a light dynamic on stator current (figure 9) and magnetic flux of d axis. It's noticed that at reduced speed of 50 rad/s, the other electric signals frequency decrease but the motor still works.

b) Overspeed operating

The motor is assigned a greater reference value than the nominal speed of asynchronous motor. Here we take 500 rad/s.

Result

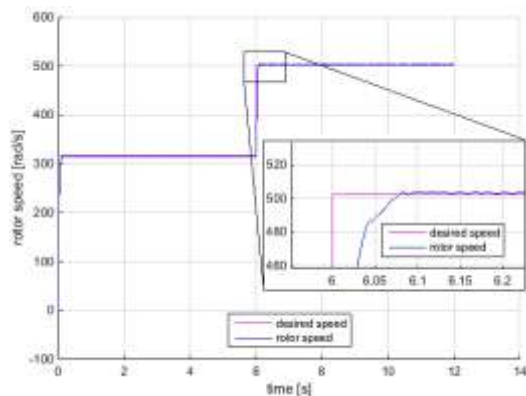


Figure 11: Rotor speed waveform

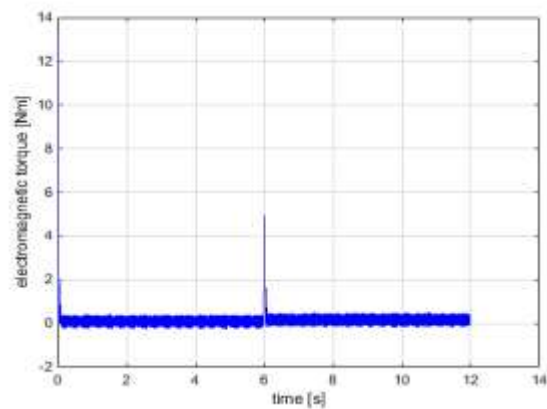


Figure 12: Electromagnetic torque waveform.

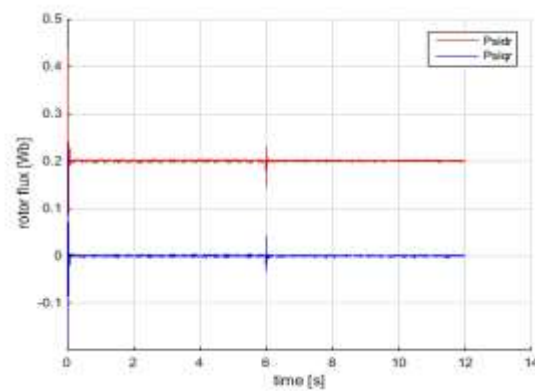


Figure 13: Rotor flux waveform.

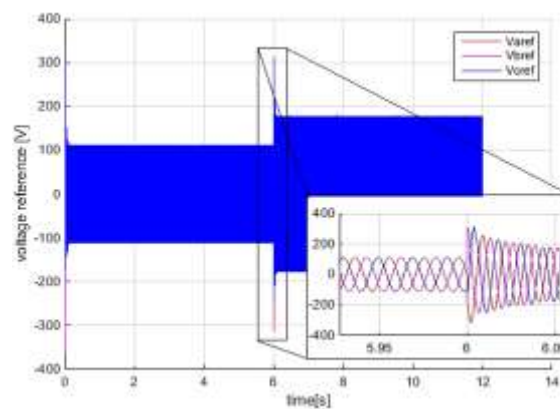


Figure 14: Reference voltage waveform

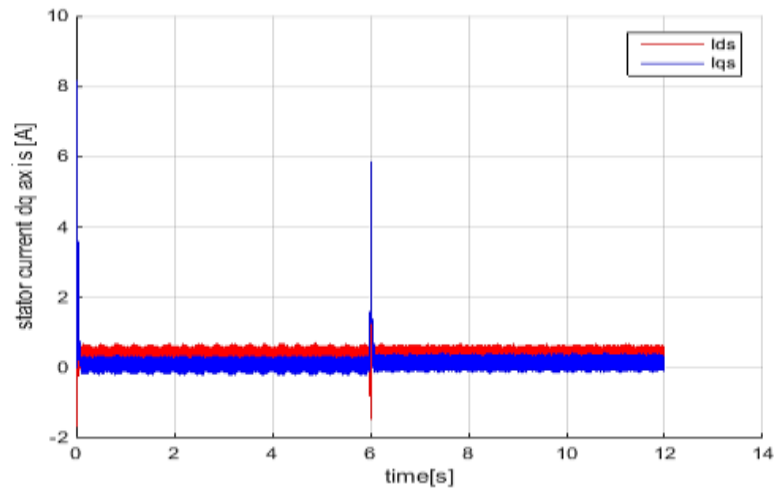


Figure 15: Stator current in dq axis waveform.

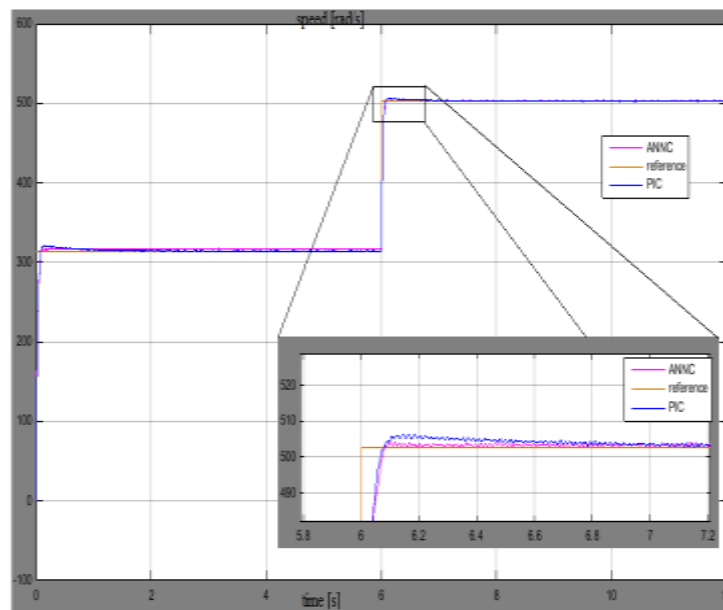


Figure 16: Speed waveforms of neural controller versus PI controller.

Discussion

The motor is fed by two-level voltage inverter with DC voltage of 300V. It works on its nominal speed of 314 rad/s when the reference changes suddenly into upper value of 500 rad/s at 6s which is seen on figure 11. It works on overspeed mode and the reference voltage increases at 175V. The controller performance is noticed by tracking the reference speed which changes quickly. A little overshoot is observed, the controller system is fast that the response time takes 0.23 s before reaching

the reference value. The figure 12, 13 and 15 depict the constancy of the electromagnetic torque, the flux and stator currents values although the speed is increased. Dynamics manifested while the reference is changed. The figure 16 conveys the performance of neural controller versus PI controller.

c) Speed inversion

The nominal speed of the motor is inverted from 314 to -314 rad/s.

- **Results**

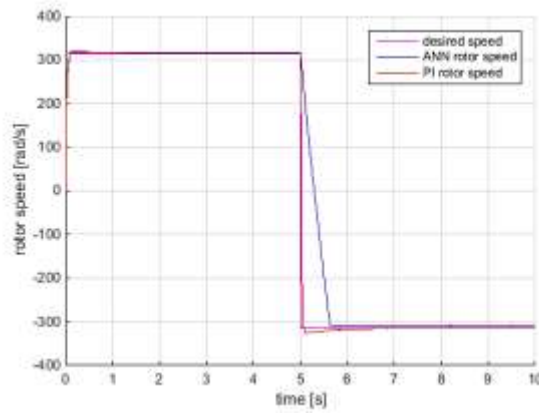


Figure 17: Rotor speed waveform of neural controller versus PI controller.

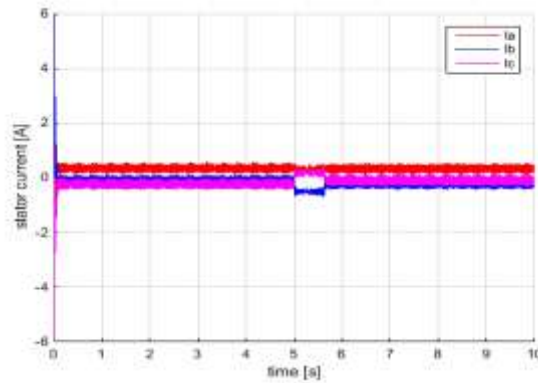


Figure 18: Stator currents waveform.

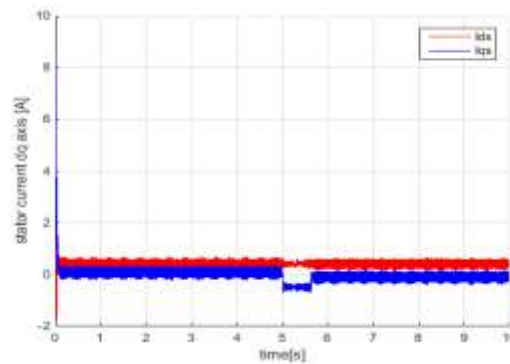


Figure 19: Stator current in dq axis

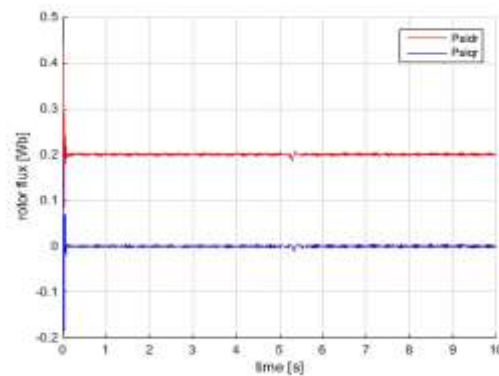


Figure 20: Rotor flux waveform

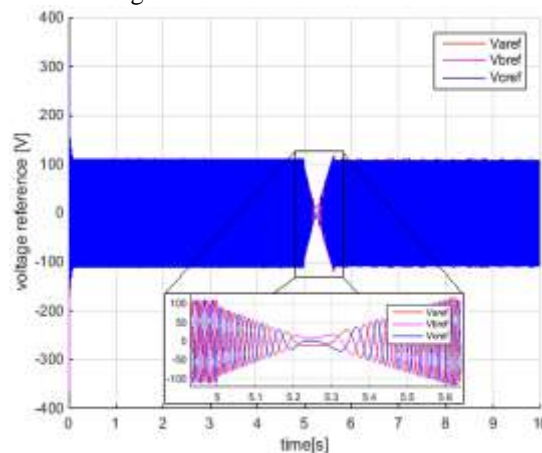


Figure 21: Reference voltage waveform.

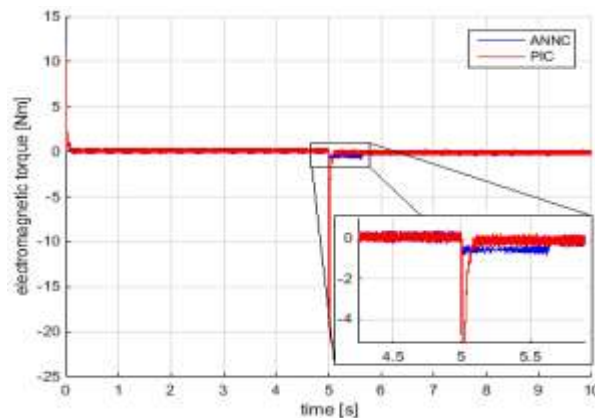


Figure 22: Electromagnetic torque waveform of neural controller versus PI controller.

- Discussion

The motor runs at nominal speed of 314 rad/s when the speed is inverted at 5s through the figure 17. No overshoot is observed when the neural controller system tracks the reference. The controller operates softly and takes 0.7 s to follow the reference speed. The figure 18 shows the exchange of stator current values when the speed is

inversed. The stator current and electromagnetic torque are increased into a constant value during the variation of the rotor speed that are showed in figure 18 and 22, the reference voltage value falls close to zero and retakes to nominal value.

2- DYNAMIC PHASE

- Résultats

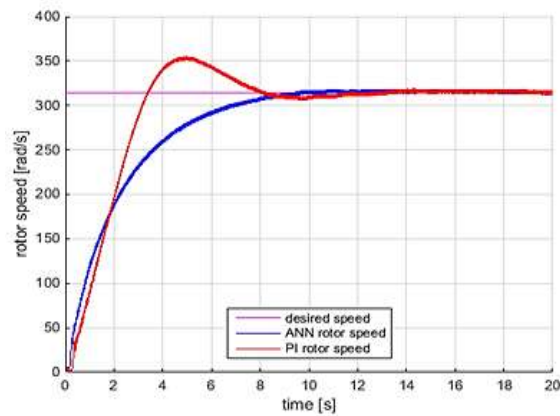


Figure 23: PI rotor speed Versus ANN rotor speed.

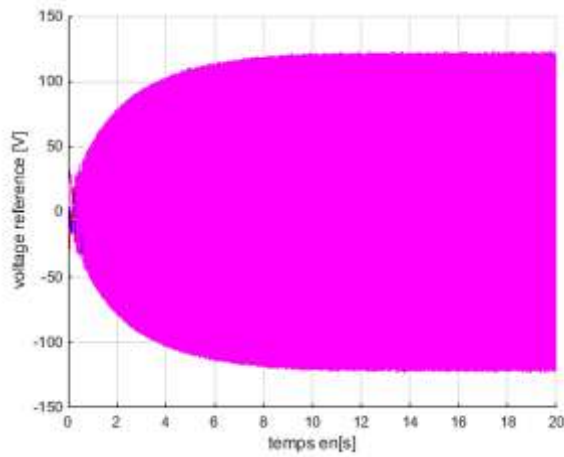


Figure 24: Voltage reference.

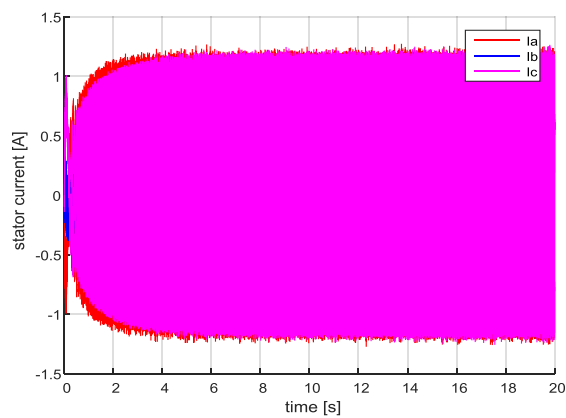


Figure 25: Stator currents.

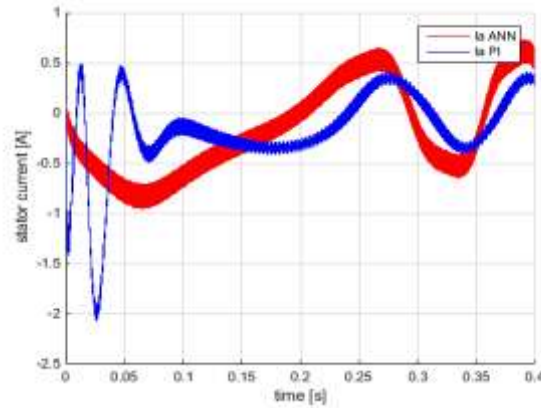


Figure 26: PI stator current versus ANN stator current.

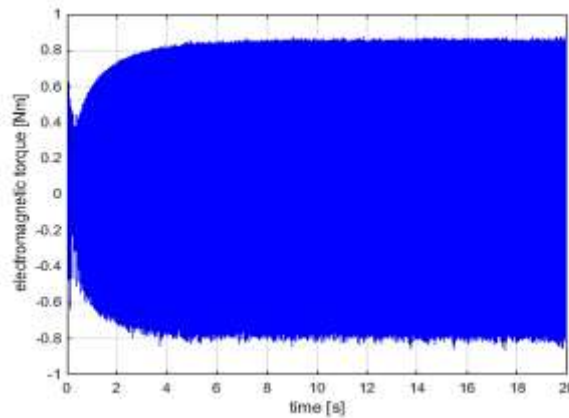


Figure 27: Electromagnetic torque.

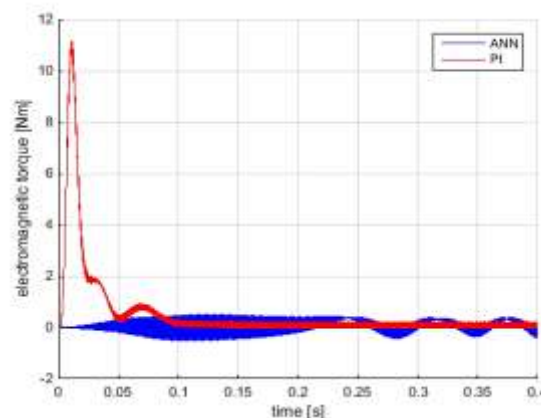


Figure 28: PI electromagnetic torque versus ANN electromagnetic torque.

Discussion

Within dynamic phase, it's observed on figure 23 that the overshoot of the speed response is high for conventional controller. This overshoot is due to the poles addition through the current controllers, the system becomes oscillating. The addition of both current controllers increases the

rotor speed response delay. The neural controller eliminates the oscillation on rotor speed. The figure 24 displays the pic of voltage reference value reduction at 30V in starting phase. Shown by the figures 25 and 26, the maximal stator current value doesn't exceed 0.9A whereas it reaches 2.1A for conventional controller. Complete reduction of

electromagnetic torque is noticed in motor starting phase by neural controller (figure 27, 28).

The results comparisons are summarized in table 1

Tableau 2: Simulation resultssummary.

Phase	Dynamic		Static (speed inversion)	
	Conventional	Neural	Conventional	Neural
I max [A]	2,1	0,9	12	0,9
n max [rad/s]	351	314	324	314
C max [Nm]	11	0,5	22	0,8

Table 3 displays the parameters used for simulations.

Tableau 3: Parameters used for simulations.

Nominalpower	¼ HP
Nominalspeed	1770 RPM
Pole	4
Statorresistance	$R_s = 12,5\Omega$
Rotorresistance	$R_r = 7,2\Omega$
Statorleakinductance	$l_s = 0,02175H$
Rotorleakinductance	$l_r = 0,02175H$
Statorcyclicinductance	$L_s = 0,49925H$
Rotorcyclicinductance	$L_r = 0,49925H$
Mutualinductance	$M = 0,4775H$
Momentofinertia	$J = 0,0022kg \cdot m^2$
Frictioncoefficient	$B = 0,001224Nm.s/rad$
Proportionalgain	$k_p = 0,1132$
Integratorgain	$K_i = 0,1652$

IX- CONCLUSION

This work described one of the neural methods for controlling dynamic systems. Brushless asynchronous motor was a dynamic system to which the proposed method was applied. Asynchronous motor mathematic model was developed with two-level voltage inverter. The principal theory of field oriented control was the backbone of the neural control one. Neural control must have passed through identification process for some control system topologies. Several tests were worked out to achieve the learning operation. The learning phase determinates the best model which generated the minimum error. The best model is served as a neural controller of the system and ensured the performance on various operating mode of the asynchronous motor. In static phase, the proposed controller proved a good performance by tracking the reference. The controller was fast, accurate and robust versus PI controller. It could prevent the machine from mechanical damage

caused by the sudden change of the reference speed and reduced the dynamics.

In dynamic phase, the neural controller eliminates the dynamics on rotor speed. It limits the stator currents and reduces the maximal value of electromagnetic torque. Consequently, the neural controller is better on controlling operation than the conventional one. It can assure a progressive starting operation without oscillation.

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