The neural controller for speed control of an indirect field oriented AC motor drive

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Abstract: - This work analyzes the hysteresis PI neural controller for speed control of an indirect rotor flux oriented controlled (IRFOC) induction motor drive. This controller generates appropriate stator current distortion in order to obtain high performance induction motor speed control. The PI controller provides better dynamic performances than the classical PI controller but it has one drawback. The hysteresis PI controller cannot deal with down step speed tracking below a certain limit. The artificial neural network generalization capacity is then used to deal with this drawback. The simulated input-output non linear relationship of the controller during startup and load disturbance rejection is learned off-line using a feed-forward linear network with one hidden layer.

Key-Words: - AC Motor, Electrical Drive, Neural Controller, Neural Network, Speed Control, Flux Oriented Controlled, Pulse with Modulation.

1 Introduction

With the apparition of the indirect rotor field oriented control (IRFOC), induction machine drives are beginning to become a major candidate in high performance motion control applications. In the complex machine dynamics, this decoupling technique permits independent control of the torque and the flux [1], [6]. The indirect rotor field oriented control is a sensitive parameter [6]. The heating and the saturation of the motor causes detuning in the decoupling operation and introduces errors in the torque and field motor output values. PID classical controllers find some difficulties in dealing with the detuning problem. Artificial neural networks (ANN) [2] can be used to design numerical controllers in order to maintain high dynamic performances even when detuning occurs.

The PI neural controller provides better dynamic performances than the classical PI controller but it has one drawback. The hysteresis PI controller cannot deal with important down step speed tracking because over certain down step reference values, the hysteresis PI generates a positive command torque that increases the motor speed when we need to decrease it [3].

The generalization capacity of the artificial neural network is then used to generalize the up step speed tracking during start up to the down step speed tracking and eliminate this drawback. The simulated input-output non linear relationship of this controller during startup and load disturbance rejection is learned off-line using an appropriate neural network in order to realize the robust neural controller.

2 Problem Formulation

The Figure 1 presents the block diagram structure of an induction motor speed control using vector reference IRFOC scheme. It consists mainly of the squirrel cage induction motor, the voltage-regulated pulse width modulated inverter, the speed controller and the IRFOC block.

The model of the squirrel-cage induction machine can be expressed in the *d*-*q* axes using the following equations:

$$\dot{X} = AX + BU, \tag{1}$$

where:

$$A=\begin{bmatrix} -\frac{1}{\sigma T_s} & \omega_s+\frac{1-\sigma}{\sigma}\omega_r & \frac{L_m}{\sigma L_s T_r} & \frac{L_m}{\sigma L_s}\omega_r \\ -\omega_s-\frac{1-\sigma}{\sigma}\omega_r & -\frac{1}{\sigma T_s} & \frac{L_m}{\sigma L_s}\omega_r & \frac{L_m}{\sigma L_s T_r} \\ \frac{L_m}{\sigma L_r T_s} & -\frac{L_m}{\sigma L_r}\omega_r & -\frac{1}{\sigma T_r} & \omega_s-\frac{1}{\sigma}\omega_r \\ \frac{L_m}{\sigma L_r}\omega_r & \frac{L_m}{\sigma L_r T_s} & -\omega_s+\frac{1}{\sigma}\omega_r & -\frac{1}{\sigma T_r} \end{bmatrix}, \qquad (2)$$

$$B=\frac{1}{\sigma L_s}\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ -\frac{L_m}{L_r} & 0 \\ 0 & -\frac{L_m}{L_r} \end{bmatrix},\ X=\begin{bmatrix} i_{ds} \\ i_{qs} \\ i_{dr} \\ i_{qr} \end{bmatrix},\ U=\begin{bmatrix} \upsilon_{ds} \\ \upsilon_{qs} \end{bmatrix}. \qquad (3)$$

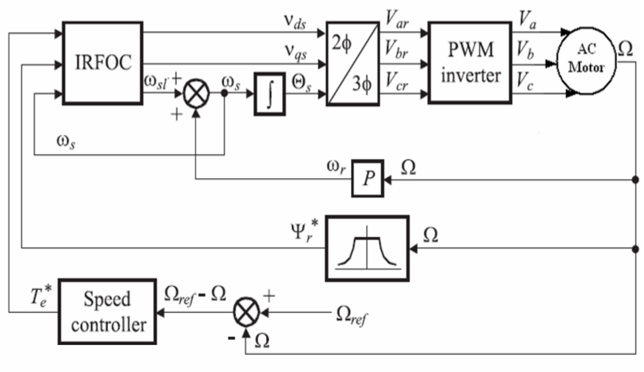

Fig. 1. The indirect rotor field orientation control.

The electromagnetic torque and the mechanical equations can be written as follows:

$$T_e=\frac{3}{2}pL_m\left(i_{dr}i_{qs}-i_{qr}i_{ds}\right), \qquad (4)$$

$$J\frac{\mathrm{d}\Omega_r}{\mathrm{d}t}+f\Omega_r=T_e-T_L, \qquad (5)$$

where J is the moment of inertia, f – the viscous friction coefficient and T_L is the load torque.

2.1 The voltage reference IRFOC Model

In the voltage reference IRFOC scheme, Figure, the command values of the electromagnetique torque, the rotor flux and the stator frequency are delivered to the IRFOC block to generate command values of the frequency and the reference voltage vector *d*-*q* frame components. The slip frequency is added to the rotor frequency and the results are integrated to evaluate the stator angle. The reference voltage vector *d*-*q* frame components along with the stator angle are delivered to the Park inverse transformation block to evaluate the reference voltage vector three phase system components. These components are delivered to a sine triangle PWM to generate pulses to the control the power switches in the inverter.

2.2 The Hysteresis PI Controller structure

The speed controller of the IRFOC block diagram from the Figure 1 is replaced with the Hysteresis PI controller presented in the Figure 2.

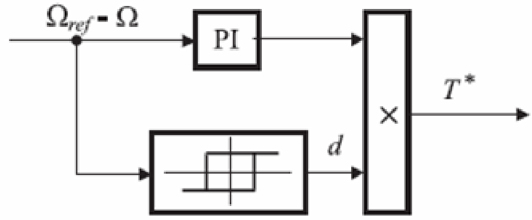

Fig. 2. The Hysteresis PI controller structure.

When the motor starts, the error is positive making the hysteresis output equal to: +1. The hysteresis PI controller acts then like a classical PI controller by decreasing the value of the speed error towards the hysteresis lower limit. When crossing this limit, the hysteresis output becomes: - 1 and changes the command torque sign.

This controller can adjust the speed of the motor only at starting mode or when load disturbances occur, it cannot deal with important down step speed tracking operation because, the hysteresis PI generates the positive command torque leading to an increase in the motor speed when we need to decrease it.

The output, $u(t)$, from the PI controller is:

$$u(t)=K_p\left[\Omega_{ref}-\Omega(t)\right]+K_i\int_0^t\left[\Omega_{ref}-\Omega(\tau)\right]d\tau, \qquad (6)$$

K_p is the proportional gain, K_i is the integral gain.

If u_k is a sample value of $u(t)$ with sampling period T_s, then for a step reference speed an approximation of u_k is given by the equation:

$$u_k=K_p\left(\Omega_{ref}-\Omega_k\right)+T_sK_i\left(k\Omega_{ref}-\sum_{i=0}^{k-1}\Omega_i\right), \qquad (7)$$

If the reference speed is reached at $I = n$ then for $k\geq n$ the hysteresis PI controller maintains the motor speed in the vicinity of the reference speed so that: $\Omega_k \approx \Omega_{ref}$. Therefore the output from the PI controller is maintained nearly constant and given by the equation:

$$u^* \approx T_S K_i \left(n\Omega_{ref} - \sum_{i=0}^{n-1} \Omega_i \right). \qquad (8$$

For the new step speed reference $\Omega_{ref\,1}$ which occurs at $t = (k+1)T_s$, on can use equation (6) to obtain:

$$u_{k+1} = u^*(K_p + T_S K_i \left(\Omega_{ref1} - \Omega_{ref} \right). \qquad (9$$

2.3 Simulation Results

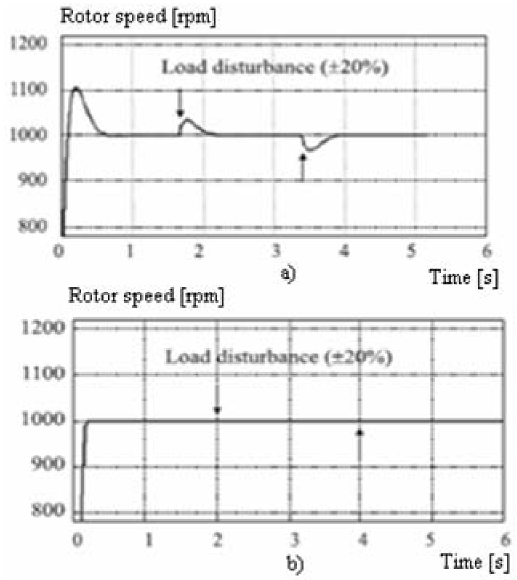

Fig. 3. Comparison performance (rotor speed) between the classical PI controller (a) and the hysteresis controller (b).

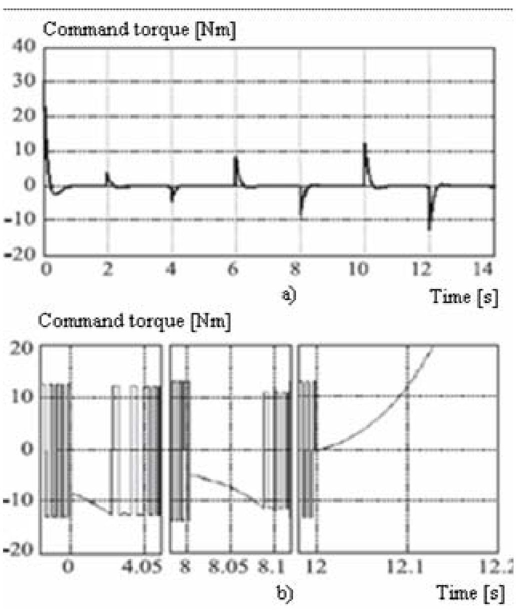

Fig. 4. Comparison performance (command torque) between the classical PI controller (a) and the hysteresis controller (b).

The Figures 3 and 4 shows the performance comparison between the classical PI controller and the hysteresis PI controller in speed control of a voltage reference IRFOC AC Motor drive.
The values of PI controller gains used are: $K_p = 0{,}4$ and $K_i = 0{,}2$ and the hysteresis limits are: ± 0,001. For simulations on used the sampling frequency of 10 kHz.
The controller input-output data obtained during simulation of the start up and load disturbance rejection could be used for the data of the neural network controller.

3 Problem Solution

The neural networks can be employed in advanced intelligent control applications by making use of their non linearity learning, parallel processing and generalization capacities [4], [5].
The neural network is constituted of densely interconnected neurons. A neuron is a computing node. It performs the multiplication of its inputs by constant weights, sums the results, shifts it by a constant bias and maps it to a non linear activation function before transferring it to its output. A feed-forward neural network is organized in layers of neurons: an input layer, one or more hidden layers and an output layer. The inputs to each neuron of the input layer are the inputs to the network. The inputs to each neuron of the hidden or output layer are the outputs from the neurons of the preceding layer.
The mathematical model of a neuron is given by follow:

$$y = \sum i = 1^n w_i x_i + b. \qquad (10$$

Where y is the output from the neuron, $(x_1, x_2, \ldots, x_n)$ are the inputs to the neuron, $(w_1, w_2, \ldots, w_n)$ are the corresponding weights, and b is the bias of the neuron. The activation function f is generally the logarithmic or tangent sigmoid function. For a logarithmic sigmoid activation function the output from the neuron is given by the equation:

$$y = \frac{1}{1 + e^{-\left[\sum_{i=1}^{n} w_i x_i + b \right]}}. \qquad (11)$$

In the supervised off-line control, the hysteresis PI controller can be replaced by the neural network that learns the mapping form of the controller input-output.
To design a neural network for a supervised off-line control, the following steps are necessary: Selection of the network structure: The number of layers, the number

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of neurons for each layer and the number of inputs to the network.

3.1 Simulation Results

The Figures 5 and 6 shows the dynamic performance comparison between the classical PI controller and the neural controller in speed control of a voltage reference IRFOC AC Motor drive.

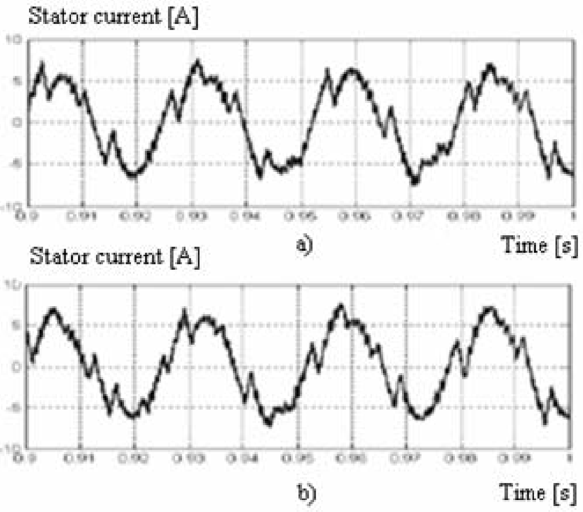

Fig. 5. Dynamic performance comparison (Stator current) between the classical PI controller (a) and the neural controller (b).

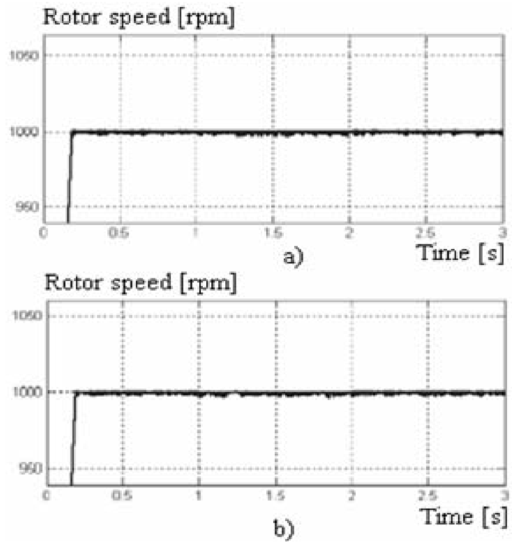

Fig. 6. Dynamic performance comparison (Rotor speed) between the classical PI controller (a) and the neural controller (b).

It is evident that the neural controller has perfectly learned the dynamic performance of the hysteresis performance PI. The steady state values of the system parameters are almost the same as obtained using the hysteresis PI. The only difference is the switching time sequence of the command torque which results in a slightly better speed control.

The neural controller is a three layers feed-forward linear network with two neurons in the input and hidden layer and one neuron in the output layer. The speed error is the only input to the controller.

4 Conclusion

The hysteresis PI speed controller for voltage reference IRFOC induction motor drive control generates appropriate stator current distortion in order to obtain high performance induction motor speed control.

The dynamic performance comparison with the classical PI controller showed that a simple hysteresis has changed the classical PI controller to a high performance controller. The only drawback is that the hysteresis PI controller cannot deal with important down step speed tracking.

The input output relationship of this controller is used to design an artificial neural network based controller whose generalization capacity got rid of the down step tracking problem.

The Simulation results show that the neural controller realizes the good dynamic behavior of the motor, with the rapid settling time, no overshoot, almost instantaneous rejection of load disturbance, the perfect speed tracking and it deals well with parameter variations of the motor. It seems to be a high-performance robust controller.

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