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SPEED CONTROL FOR THREE PHASE INDUCTION MOTOR USING ADALINE NEURAL NETWORKS

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Abstract: The speed control of the three phase induction motor is still a challenging problem. Although the results obtained by means of the conventional control are very good, many researches in this area are ongoing. The authors propose a different control approach based on artificial intelligence. The control signals for speed, torque and flux regulation are computed using three ADALINE (Adaptive Linear Neuron) neural networks. The numerical simulations are made in Simulink and the obtained results are compared with the conventional drive approach (cascaded PI controller).

Keywords: ADALINE neural network, three phase induction motor, Matlab / Simulink.

1. INTRODUCTION

The induction motor drive systems (IMDS) are used on a very large scale in industrial applications. The metallurgic domain uses them widely in cold rolling mills for example (Roman, 2011). However, gradually the IMDS started to be used also in domestic area, especially in rural areas. The induction motors can successfully be applied in applications which include air conditions, elevators, pumps for irrigation or drinking water, washing machines, machinery for mills or small industries, etc.

Over the years, different control approaches for the IMDS had been proposed. Nevertheless, the classical ones, involving PI controllers (Leonhard, 2001) remain widespread because of the decent performances combined with the easiness in the implementation. However, if the system has uncertainties or un-modeled nonlinearities the PI controllers might not give the best results. Therefore, different approaches, based on artificial intelligence, has been proposed in the literature, like: the use of fuzzy logic in the speed controller implementation (Woo-Yoog Han, 2003), genetic algorithms (Anandaraju, 2011), evolutionary computing (Anandaraju, 2012), neuro-fuzzy techniques (Wai, 2008; 2013), different architectures of ANN for speed estimation and control (Kim, 2001; Kuchar, 2004; Maiti, 2012; Girovský, 2012)

In order to use artificial neural networks (ANN) as a part of the control systems for IMDS a real time control should be achieved. Therefore, a very simple ANN should be used. The proposed ANN does not require complex computing (is the case of ADALINE network). As alternatively, a very powerful computer should be available (can be a DSP board or neural processor) to compute the ANN output in a shorter time than sampling time of the controlled system. As a conclusion for this paragraph, based on different

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drive simulations which imply ANN good results could be obtained, but the real challenging problem is to apply them to the real systems.

This paper is structured as follows: in Section 2 the Rotor Field Oriented Control of the IM is presented, in Section 3 some details of the ADALINE neural networks are shown. Section 4 is dedicated to the implementation of ADALINE controllers and simulation results. The last Section draws the conclusions of the paper, but also future directions of researches are highlighted.

2. THE ROTOR FIELD ORIENTED CONTROL OF THE INDUCTION MACHINE

Adjustable asynchronous machine drives raises several issues related to static power converters supply, and control complexity. The most important issue is to control the electromagnetic torque. In order to adjust the electromagnetic torque the field oriented control is involved. The principle is based on the torque deduction knowing the invariance property to the reference frame changes. By using the dq synchronous reference frame, aligned with the rotor magnetizing current, the electromagnetic torque becomes (Leonhard):

$$(1)\quad T_e = \frac{3}{2} p \Psi_{mr} i_{sq}$$

In this way, the active and reactive stator current active current components separate the mechanical phenomena by the magnetic one. Below the rated speed the rotor flux is maintained at the constant value. Therefore, the electromagnetic torque turns into an appropriate expression:

$$(2)\quad T_e = K_M i_{sd\lambda},\ K_M = \frac{3}{2} p \Psi_{mr}$$

The differential equations of the three-phase induction motor in field rotor oriented control are as follows:

$$(3)\quad \begin{aligned} &\tau_R \frac{di_{mR}}{dt} + i_{mR} = i_{sd} \\ &T_e = \frac{2}{3} p \frac{M}{1+\sigma_R} i_{mR} \cdot i_{sq} \\ &\frac{J}{p} \frac{d\omega_e}{dt} = T_e - \frac{F}{p} \omega_e - T_l \\ &\frac{dq}{dt} = \frac{1}{p} \omega_e + \frac{i_{sq}}{\tau_R \cdot i_{mR}} \end{aligned}$$

where:

i_{sd} the longitudinal component stator current;
i_{sq} the transversal component stator current;
i_{mR} the magnetizing current;
ω_e the electrical angular velocity of the rotor;
T_e electromagnetic torque of the induction motor;
T_l load torque;
q the angular position of the rotor field;
J the combined inertia of the motor and load;
F the viscous friction coefficient;
M mutual inductance between the stator and rotor d,q equivalent windings;
τ_R the rotor time constant;
σ_R the rotor leakage factor;
p the number of pole pairs.

The field oriented drive system consists of the mechanical loop control and of rotor magnetizing flux loop control. The inner loop of the speed control consists of the torque loop. By using the direct Clarke and Park transformations the three phase voltages are transformed into synchronous reference frame two phase system (d,q). The rotor field (d,q) voltage components are using as inputs into the voltage mathematical model (Fig.1). The outputs of the voltage model are the two-phase stator currents in synchronous reference frame. Based on the current model of the IM, the magnetizing rotor current and the rotor field angular position are found. These quantities are used as feedback components in order to compare with the appropriate references (Fig.2).

As a result, the conventional vector control of the IM consists of a cascaded control in which each state variable is independently controlled. By using the magnitude criterion for the inner loops, the parameters of Proportional Integral (PI) controllers are found. For the outer loops, the symmetry criterion conducts to the adequate parameters of the controllers.

The rotor field oriented control can assure the speed greater than the rated one. Therefore, the speed is increased upon the maximum speed limit. This operating regime is named flux weakening. During the flux weakening control the constant power is assured.

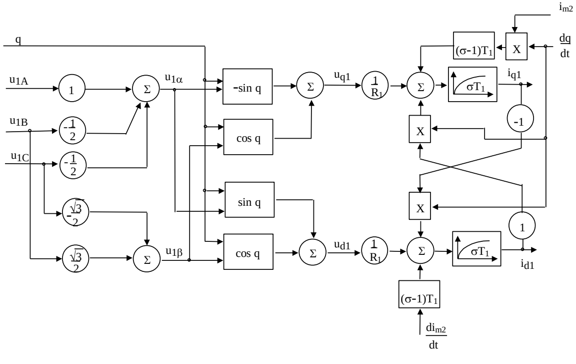

Fig.1. Voltage mathematical model

The rotor field voltage references are sent to the stator coils through the inverse Park and Clarke transformations. The Pulse Width Modulator (PWM) delivers the imposed duty-cycles to the driver circuit. The power inverter delivers the adequate three-phase voltages to the three-phase induction machine.

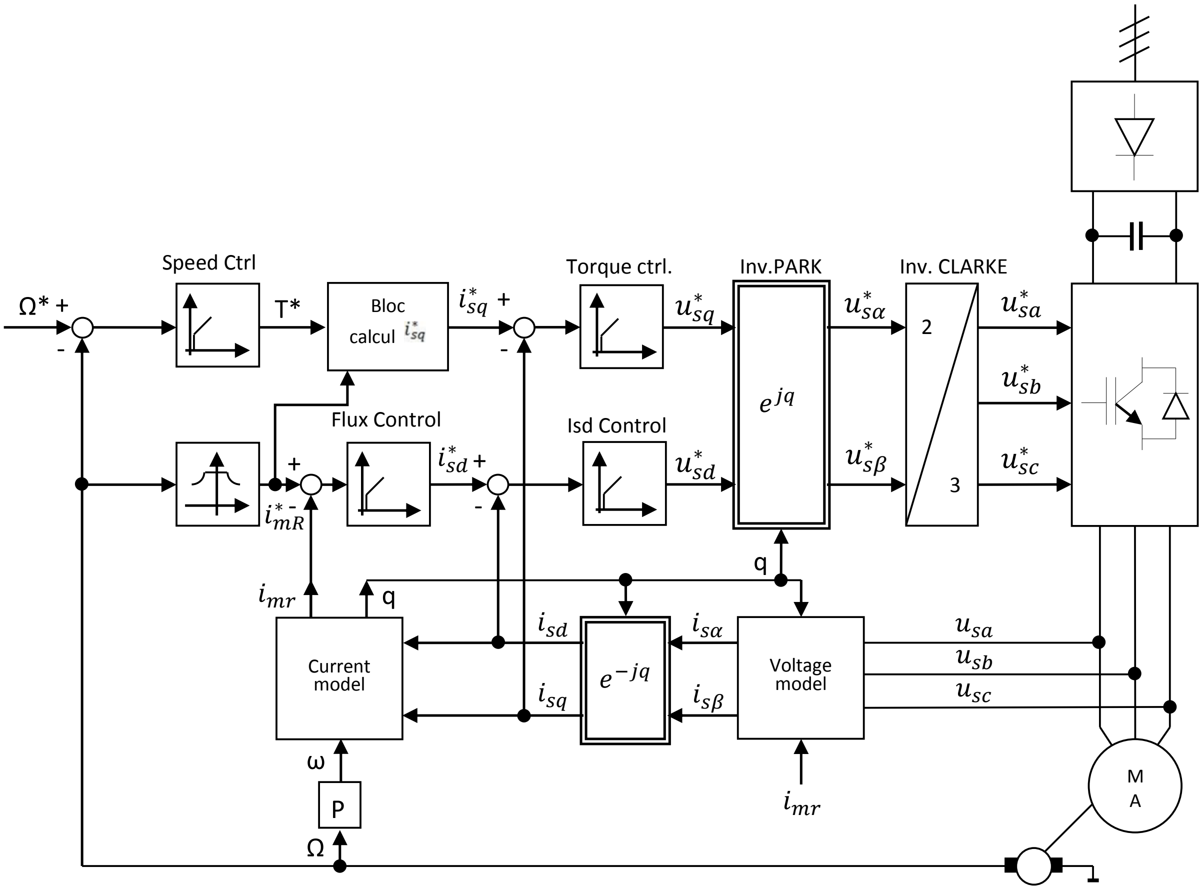

Fig.2 Rotor field oriented control of the IM

3. THE ADALINE NETWORK

The ADALINE network is similar to a perceptron, with the difference that the transfer function is linear in contrast with the hard-limiting function used by perceptron. This allows their output to take any value, instead of limited interval like in the case of perceptron. The ADALINE model is presented in Figure 3.

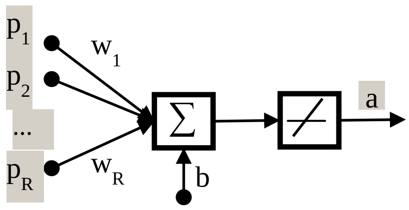

Fig.3 The ADALINE network

where:

p – is the input vector

w – is the weights matrix of the network

b – is the bias of the network

a – is the output of the network

The output of the network is computed with the following relation:

$$(4)\ a = purelin\,(\boldsymbol{wp} + b) = \boldsymbol{wp} + b = w_1 p_1 + w_2 p_2 + \cdots + w_R p_R$$

Usually, the ADALINE network uses for training the Widrow-Hoff algorithm (Widrow, 1960) or Least Mean Square (LMS) algorithm to adjust the weights and the bias in order to minimize the mean square error (MSE). The MSE for the ADALINE network is:

$$(5)\ MSE = \frac{1}{R}\sum_{j=1}^{R} e(j)^2 = \frac{1}{R}\sum_{j=1}^{R}(t(j) - a(j))^2$$

where *t* is the desired output of the network.

One of the main disadvantages of LMS is that doesn’t guarantee the find of the global minimum, excepting the situations when there’s only one minimum. That is the case of ADALINE network, she have only one minimum. Therefore, no matter what are the initial random values of the weights and bias, the LMS algorithm will always find the global minimum.

The relations for adjusting the weights and the bias are the followings:

$$(6)\ \Delta w_j = w_j(k+1) - w_j(k) = -\alpha \frac{\partial e^2(k)}{\partial w_j}$$

where k – iteration number and $j = \overline{1, R}$

$$\frac{\partial e^2(k)}{\partial w_j} = 2e(k)\frac{\partial e(k)}{\partial w_j} = 2e(k)\frac{\partial[t(k) - a(k)]}{\partial w_j}$$

$$= 2e(k)\frac{\partial[t(k) - (\sum_{j=1}^{R} w_j p_j(k) + b)]}{\partial w_j} = -2e(k)p_j(k)$$

$$(7)\ \Delta w_j = -\alpha\left(-2e(k)p_j(k)\right) = 2\alpha e(k)p_j(k) = \eta e(k)p_j(k)$$

where η is the traditional notation for the learning rate.

Similarly we can write the descent rule for adjustment of the bias:

$$(8)\ b_j(k+1) = b_j(k) + \eta e(k)$$

These rules can be easily extrapolated if we have an ADALINE network with more than one layer. Also some variations of the basic steepest descent rule, such as sigma modification, e-modification, dead zone and projection (Polycarpou, 1998) can guarantee the ultimate boundedness of both estimation error and network weights, in presence of noise and uncertainty.

4. SIMULATION RESULTS

To prove the effectiveness of the proposed ADALINE controllers, in figure 4 the detailed control block is depicted. The overall Simulink scheme of IMDS is the same as one detailed in Costin *et. al.* (2009).

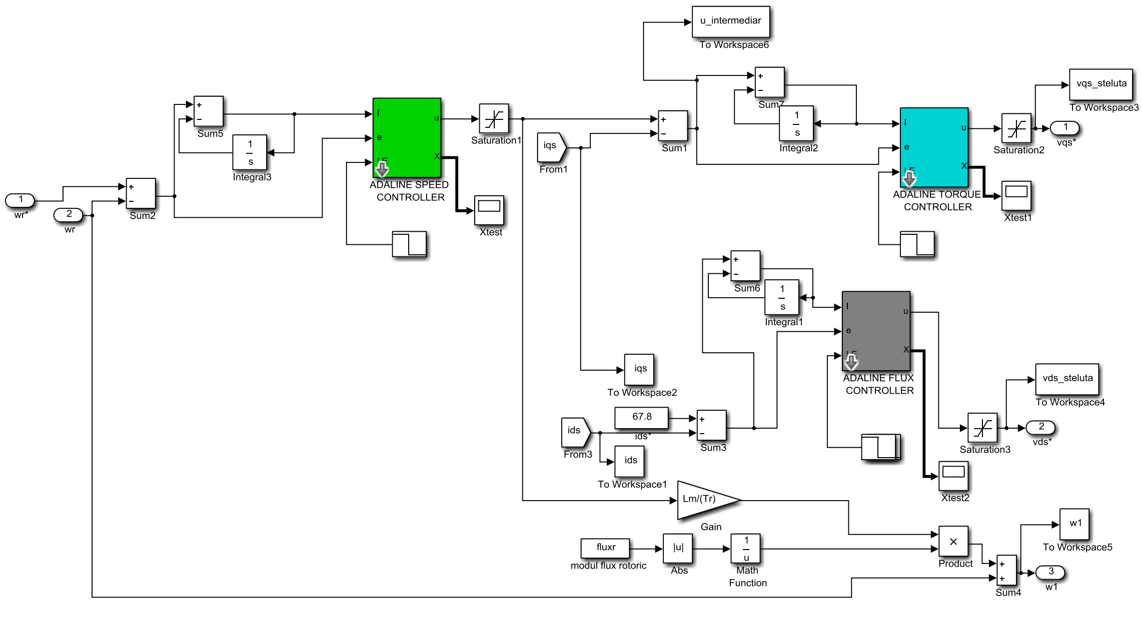

Fig.4 The detailed Simulink scheme of Control Block

The control structure includes three ADALINE controllers: one for the rotor speed, one for the torque and one for flux regulation). All three ADALINE controllers can be seen as adaptive PI controllers. The ADALINE blocks are modified controllers which are detailed in Campa (2002).

The **inputs** to any ADALINE block are the followings:
- The error between the real output and the network approximation which should emulate the proportional component
- The sum of current error and the previous error which should emulate the integral component
- A logic signal that enables/disables the learning. In our case, the learning process is always enabled, so that the weights of the network adapt at every step.

The **outputs** of any ADALINE block are the followings:
- The control signal.
- All the “states” of the network namely the weights and all the parameters that change during the learning process.

The results of the rotor speed control are depicted in figure 5. For the comparison, the control results obtained by using three PI controllers are chosen. The methodology of PI controllers tuning is not covered by this paper. Their implementation is already detailed in Costin *et. al.* (2009) and Găiceanu *et. al.* (2013).

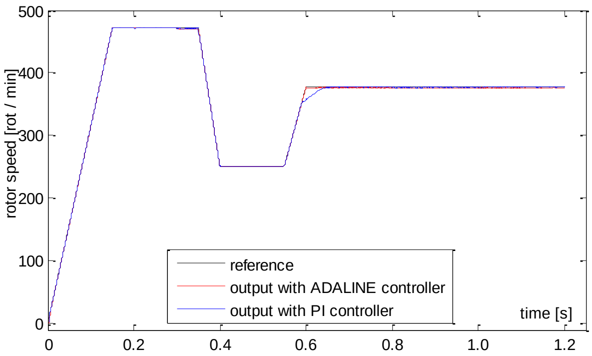

Fig.5 The reference and real rotor speed signals

However, by using the magnifying tool from Matlab (Fig. 6) some differences between the two control methods of the rotor speed (ADALINE and PI) can be seen.

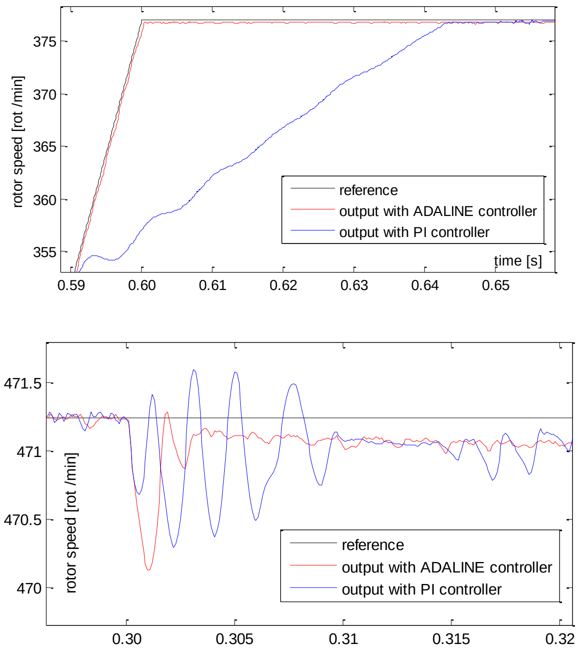

Fig.6 Reference and real rotor speed signals (magnified)

At the time 0.2s the 20Nm step load torque is initiated (Fig. 7), the both electrical drive system, based on PI and ADALINE controllers tracks very well the imposed reference speed (steady state error becomes almost zero-Fig.8).

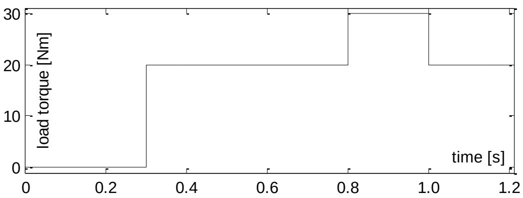

Fig.7 The load torque

The rotor speed error signal (for speed control, when using PI controllers and ADALINE controller) is depicted in Figure 8.

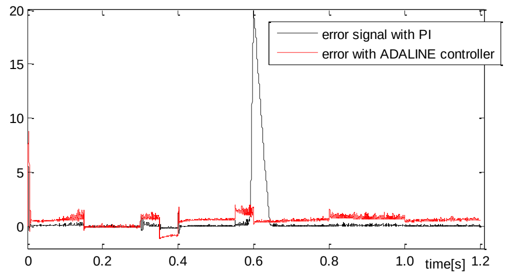

Fig.8 The rotor speed error signal

The evolutions of each controller's parameters are shown in figure 9. Each of the three ADALINE controllers has 2 weights which correspond to the proportional and integral components.

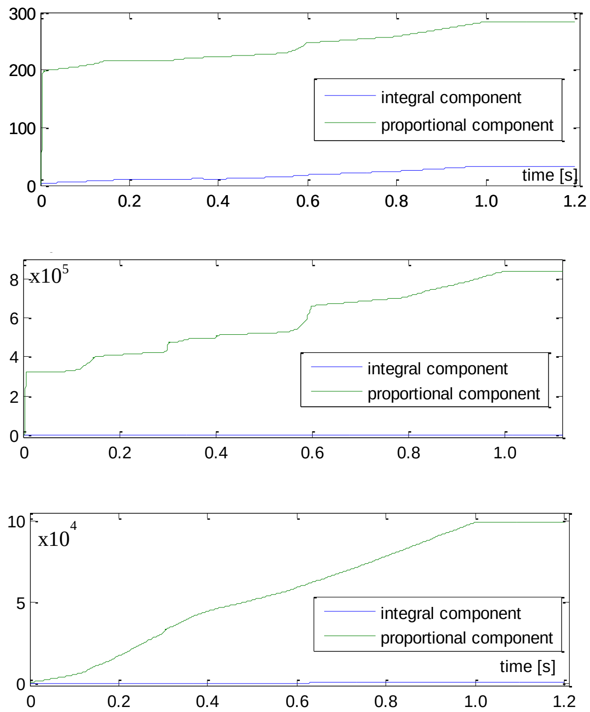

Fig.9. The evolution of each controller' parameters

5. CONCLUSIONS

The comparison between the conventional and the intelligent control are shown this paper. The conventional control consists of the cascaded PI controllers. The intelligent control consists of the artificial neuronal network.

The idea of using ADALINE networks to control the speed, the torque and the flux proves to be very good based on our simulations. The ADALINE networks are trained online and acts just like adaptive PI controllers.

Both controller schemes (PI and ADALINE) shows good robustness when an external disturbance (load torque) becomes active.

The using of the ADALINE control improves the vector control of the IM due to its capabilities to adapt to the changes of the IM.

The future works will involve the implementation of the proposed control into a real time IMDS. Also the authors will investigate the benefits of using recurrent neural networks as controllers.

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