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Speed-Sensorless Control of Induction Motor Drive using MRAS-Neural Self-Tuning IP Obsrever

***Abstract**. A speed-sensorless control of induction motor drive based MRAS-Neural Self-Tuning IP Observer is proposed. A Model Reference Adaptive Systems speed observer can give good rotor speed estimation, but speed errors will occur during low speed. In this work the rotor speed is estimated using MRAS-Neural Self-Tuning IP obsrever. The simulation results illustrate the good performance and the validity of the proposed observer scheme for practical applications.*

Streszczenie.** W artykule opisano bezczujnikowe sterowanie napędem indukcyjnym bazujące na somostrojacym się oserwatorze wykorzystującym sieć neuronową MRAS. Zazwyczaj przy małych prędkościach wirnika pojawia się błąd pomiaru prędkości. W proponowanej metodzie udaje się ten błąd wyeliminować. **Bezczujnikowe sterowanie napędem indukcyjnym przy wykorzystaniu sieci neuronowej MRAS

Keywords: Induction Motor, Sensorless, Model Reference Adaptive System (MRAS), Neural Self-Tuning IP Observer.
Słowa kluczowe: sterowanie bezczujnikowe napędem indukcyjnym, system adaptacyjny MRAS, sieć neuronowa.

Introduction

Induction motors are widely used in many industrial applications due to their self starting capability, simple structure, mechanical robustness and low cost. However, the high nonlinearity and time-varying nature of an induction motor drive demands fast switching power devices and a large amount of real-time computation. The most used control systems of induction motor is the field oriented control method. The FOC method presents some high standards in modern industrial drives [1]. The research in control of induction motors during the last years has been on sensorless solutions. In such control schemes, the motor is controlled without measuring its speed, making the system less expensive and unaffected by sensor failures, maintaining at the same time the advantages that the induction motor has with respect to other electric machines [2]. The rotor speed estimation is reconstituted by MRAS Observer. Model reference adaptive system scheme is important since it leads to a relatively easy-to-implement system with high speed of adaptation. The MRAS observer method is more attractive to estimated the rotor speed [3]. The application of artificial neural network attracts the attention of many scientists from all over the word. The reason for this trend is the many advantages which the architectures of ANN have over traditional algorithmic methods. Among the advantages of ANN are the ease of training and generalization, simple architecture and possibility of approximating non linear functions [4]. In this work, the artificial neural network is included in MRAS. The robustness of the control for induction motor drive is ameliorated by this proposed sensorless control scheme. The proposed sensorless control scheme is tested via MATLAB Simulink and its efficacy in tracking is verified.

This paper is structured as follows: Firstly the sensorless control is presented in section 2. Section 3 describes the scheme of proposed MRAS-Neural Self-Tuning IP obsrever. In section 4 we give some comments and discussion of the simulation results. Finally, conclusions are given in sections 5.

Induction motor modelling

The dynamic models of induction motor are described by set electrical and mechanical non-linear differential equations [5]. Using the Park transformation the three-phase stator windings (A,B,C) can be transformed into equivalent quadratic-phase windings (d,q).

$$\frac{d}{dt}i_{sd} = \frac{1}{\sigma \cdot L_s}\Big[-\big(R_s + \frac{L_m^2}{L_r \cdot T_r}\big)\cdot i_{sd} + \omega_s \cdot \sigma \cdot L_s \cdot i_{sq} + \frac{L_m}{L_r \cdot T_r}\cdot \phi_{rd} + \frac{L_m}{L_r}\cdot \omega_r \cdot \phi_{rq} + V_{sd}\Big] \tag{1}$$

$$\frac{d}{dt}i_{sq} = \frac{1}{\sigma \cdot L_s}\Big[-\omega_s \cdot \sigma \cdot L_s \cdot i_{sd} - \left(R_s + \frac{L_m^2}{L_r \cdot T_r}\right)\cdot i_{sq} - \frac{L_m}{L_r}\omega_r \cdot \phi_{rd} + \frac{L_m}{L_r \cdot T_r}\cdot \phi_{rq} + V_{sq}\Big] \tag{2}$$

$$\frac{d}{dt}\phi_{rd} = \frac{L_m}{T_r}\cdot i_{sd} - \frac{1}{T_r}\cdot \phi_{rd} + (\omega_s - \omega_r)\cdot \phi_{rq} \tag{3}$$

$$\frac{d}{dt}\phi_{rq} = \frac{L_m}{T_r}\cdot i_{sq} - (\omega_s - \omega_r)\cdot \phi_{rd} - \frac{1}{T_r}\cdot \phi_{rq} \tag{4}$$

$$\frac{d}{dt}\omega = \frac{P^2 \cdot L_m}{L_r \cdot J}\left(i_{sq}\phi_{rd} - i_{sd}\phi_{rq}\right) - \frac{F}{J}\omega - \frac{P}{J}C_r \tag{5}$$

where:

$$\sigma = 1 - \frac{L_m^2}{L_s L_r}, \; T_r = \frac{L_r}{R_r}$$

s, r - stator and rotor subscripts; d, q - direct and quadrate Park subscripts; P - number of pole pair; F - coefficient of friction; J - moment of inertia; L_s, L_r - stator and rotor inductances; L_m - mutual inductances; R_s, R_r - stator and rotor resistances; T_r - stator and rotor time constants; C_r - load torque; v, i - voltage and current; ϕ - flux linkage; ωs - stator frequency; ω ,ω_r - rotor speed and rotor angular speed

Control Speed

Field oriented control technique is intended to control the speed of induction motor. This strategy provides a linear and decoupled control between the flux and torque of the induction machine.

In the vector control scheme, The rotor flux is controlled by PI controller taking as input the reference value ϕ_r* and the calculated value. The axes being decoupled, it is common to use two similar PI controllers for computing the stator references voltages. The speed control is usually performed by a PI controller, its role being to minimize the error between the reference speed and measured value [6].

The direct vector control scheme is better explained by figure 1.
where: α, β - Alpha and Beta subscripts; ^ - Superscript of estimated quantity; e - Error ; C_e - Electromagnetic torque; ω_{ref} - Reference speed.

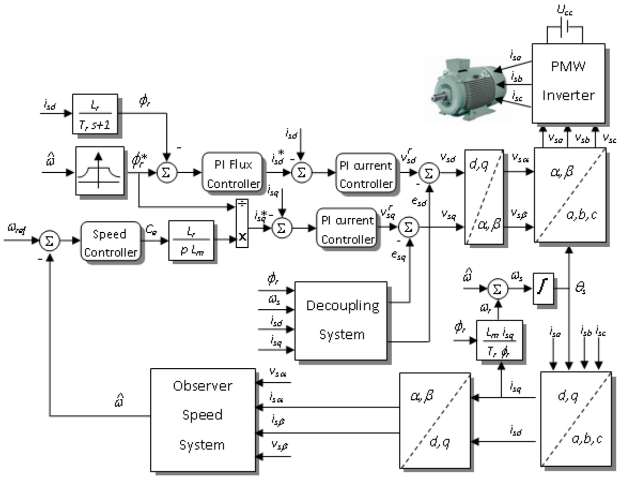

Fig.1.Direct field-oriented control for induction motor equipped with observer speed system

Observer system

We estimate the speed by using model reference adaptive systems observer represented in figure 2. This adaptive observer estimate the rotor speed by uses two models. The model that does not parameters to be estimated is named as a reference model. The model that has parameters to be estimated is named as a adaptive model. The output of the adaptive model is compared with that of the reference model, and the difference is used to estimate the speed [7],[8].

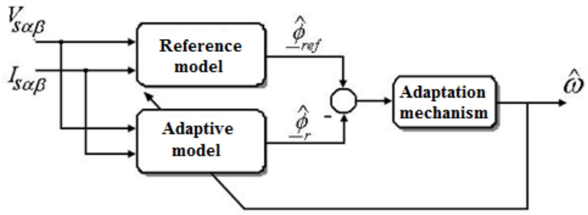

Fig.2.Structure of model reference adaptive systems

The reference model is given by:

$$\text{(6)}\qquad \begin{cases} \phi_{r\alpha} = \dfrac{L_r}{L_m}\left(\int\left(v_{s\alpha} - R_s i_{s\alpha}\right)dt - \alpha L_s i_{s\alpha}\right) \\ \phi_{r\beta} = \dfrac{L_r}{L_m}\left(\int\left(v_{s\alpha} - R_s i_{s\beta}\right)dt - \sigma L_s i_{s\beta}\right) \end{cases}$$

The adaptive model is given by:

$$\text{(7)}\qquad \begin{cases} \dfrac{d\,\hat{\phi}_{r\alpha}}{dt} = -\dfrac{1}{T_r}\hat{\phi}_{r\alpha} - \hat{\omega}\,\hat{\phi}_{r\beta} + \dfrac{L_m}{T_r} i_{s\alpha} \\ \dfrac{d\,\hat{\phi}_{r\beta}}{dt} = -\dfrac{1}{T_r}\hat{\phi}_{r\beta} + \hat{\omega}\,\hat{\phi}_{r\alpha} + \dfrac{L_m}{T_r} i_{s\beta} \end{cases}$$

The adaptation mechanism compares the two models and estimates the speed of rotation by an integral proportional regulator. Using Lyapounov stability theory, we can construct a mechanism to adapt the mechanical speed from the asymptotic convergence's condition of the state variables estimation errors [4].

$$\text{(8)}\qquad \begin{cases} e_\omega = \hat{\phi}_{r\alpha}\,\phi_{r\beta} - \hat{\phi}_{r\beta}\,\phi_{r\alpha} \\ \hat{\omega} = \left(k_{pw} + \dfrac{k_{i\omega}}{p}\right)\cdot e_\omega \end{cases}$$

Kp and Ki are positive gains.

The proposed MRAS-Neural Self-Tuning IP Observer

Neural network is inspired from biological system [9],[10].The neural networks are known for their capacity of classification [11],[12]. In our work, the multilayer back propagation feed forward neural network has been used to develop a novel model that provides good estimation of parameters K_p and K_i for IP controller. The mathematical structure of used in this paper has been shown in Figure 4 [13].

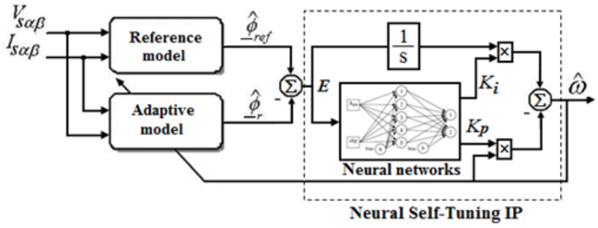

Fig.4.Structure of MRAS-Neural Self-Tuning IP obsrever

Several networks were tested. The Figure. 4 shown the ANN model used. The error e is used as input and K_p, K_i are used as output. These input and output readings have been provided from the conventional IP controller readings. Therefore the network is a multilayer perceptron (MLP) where its architecture is represented on figure. 5. It is composed of one input neuron, one hidden layer of five neurons and two outputs neurons. The design of the network and selection of optimum training parameters are performed by trial and error. The training algorithm used in this work is the gradient backpropagation. Figure 6 shows the evolution of the error during the training phase of the neurons network. After training, one found that the convergence is faster and the results are reliable.

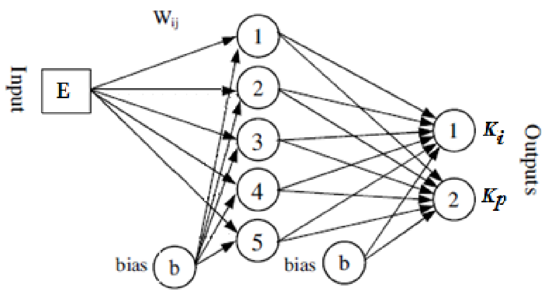

Fig.5.Neural netwok architecture

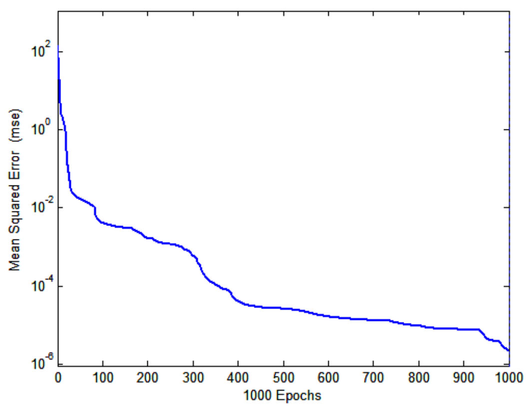

Fig.6.Evaluation of the error during the learning phase

Discussion of the simulation results

The described control structure shows in Figures 1 and 4 was implemented in the environment software MATLAB/SIMULINK, and tested in various operating conditions. The parameters values of the system under study are summarized in table 1. A combined plot of the reference speed input, estimated rotor speed and measured rotor speed is shown in Figure 7. The reference speed input is a ramp rising from zero to a positive input value of 100 rad/s and falling back to a negative input value of -100 rad/s and then to 50 rad/s. The external force (under varying-load conditions) of 10 N.m is implicated at t =2 sec and eliminated at t = 3 sec and this force is changed to 2 N.m and eliminate at t=6 sec and at t=9 sec respectably. As can be seen, ramping provides a gradual speed transition, thereby enabling the estimated rotor speed and measured rotor speed to tracking the reference speed input. The coefficients kp and ki delivered by the neural networks are variable and fits properly to speed changes.

Table 1. The parameters of induction motor

Parameters	Values	Units
Power	1.5	kW
Frequency	50	Hz
Voltage Δ/Y	220/380	V
Current Δ/Y	2.8/4.8	A
Motor Speed	1420	RPM
Pole pair (p)	2	
R_s	4.85	Ω
R_r	3.805	Ω
L_s	0.274	H
L_r	0.274	H
L_m	0.258	H
J	0.031	Kg.m2
F	0.00114	Kg.m/s

Figure 8, shown the speed errors (first: difference between the reference speed and measured speed, second: difference between the reference speed and estimated speed). Heavy loading causes higher transient speed errors due to high instantaneous speed changes where light-loading speed errors are much smaller in nominal conditions speed.

In Figures 9 and 10 the generated electromagnetic torque and stator current are shown. The reference torque and the electromagnetic torque are equal. The values of current are acceptable and the decoupling is well maintained.

Figures 11, 12, 13 and 14 shows the performance of the proposed speed sensorless drive scheme in at a very low speed 20 rad/sec, -20 rad/sec and 10 rad/sec under load conditions of 2 N.m. The speed outputs obtained are very smooth with negligible speed errors. These results show clearly very satisfactory that the proposed structure has good speed estimation and adequate vector control characteristics at low rotor speed operation.

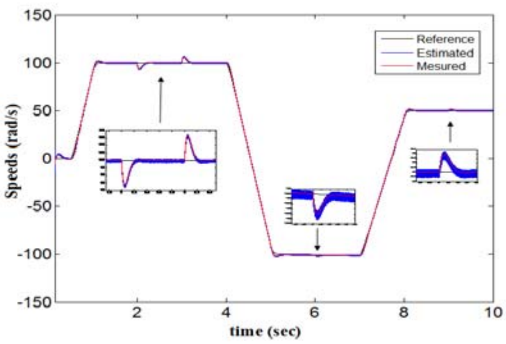

Fig.7 Performance of MRAS-Neural Self-Tuning IP obsrever with speed reverse and load charge change

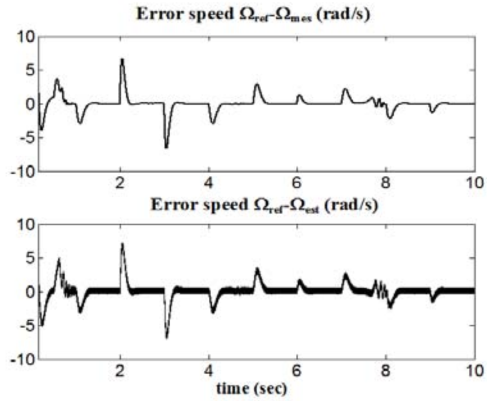

Fig.8 Speeds errors of the induction motor

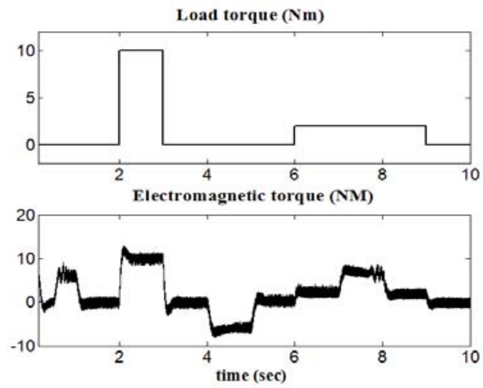

Fig.9 Electromagnetic torque of the induction motor

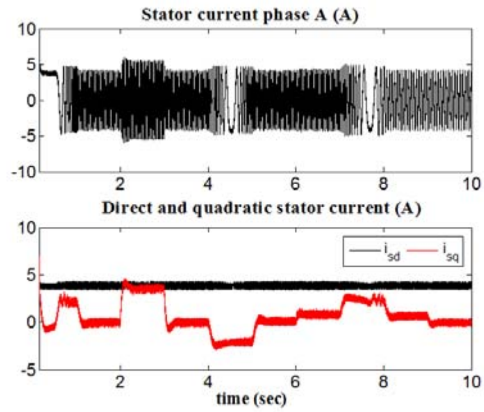

Fig.10 Stator currents of the induction motor

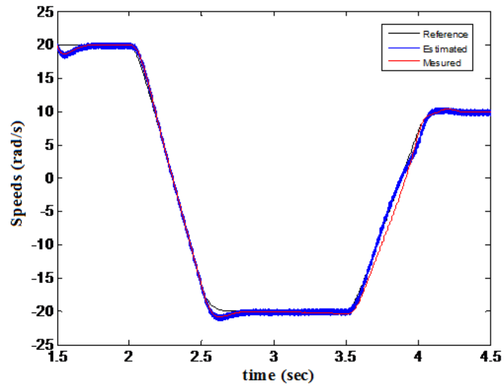

Fig.11 Performance of MRAS-Neural Self-Tuning IP obsrever with low speed region during speed reversal

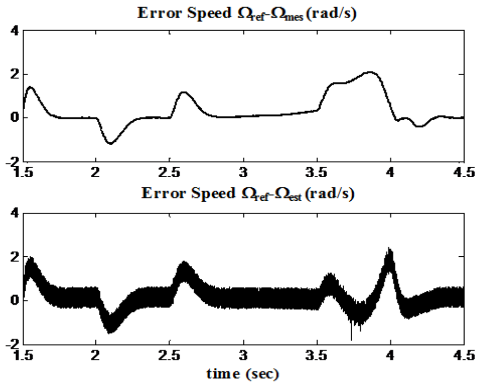

Fig.12 Speeds errors of the induction motor with low speed region during speed reversal

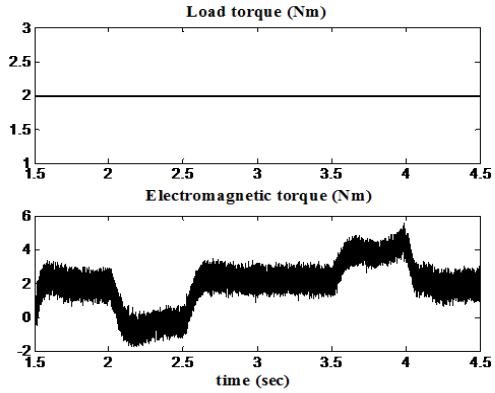

Fig.13 Electromagnetic torque of the induction motor with low speed region during speed reversal

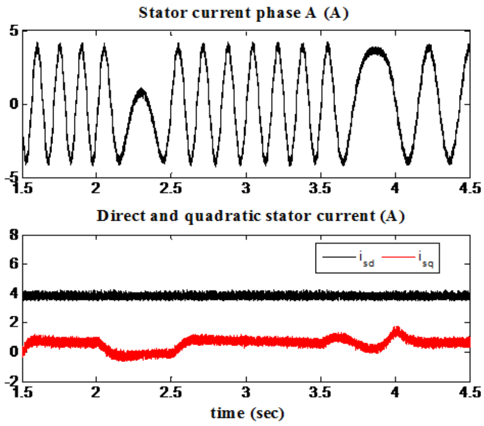

Fig.14 Stator currents of the induction motor with low speed region during speed reversal

Conclusion

In this paper, we have validated the online estimation for the rotor speed of an induction motor based on a new approach MRAS- Neural Self-Tuning IP observer. Thus, this approach is proposed for solving the problem of observer for rotor speed in at a very low speed. The proposed scheme was analyzed, designed and validated through simulation results. These results show clearly very satisfactory performance for the proposed sensorless controller in tracking and a remarkable pursuit between measured and estimed speed of the reference model speed and a perfect decoupling.

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