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COMPARATIVE ANALISE OF OPTIMAL MRAS SPEED IDENTIFICATION

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Abstract: *The paper deals with comparative analise of optimal Model Reference Adaptive System for speed identification in indirect vector control scheme of induction motor. Proportional integral controller has been optimized via Genetic algorithm, Partical swarm optimization and Simulated annealing. Experimental results are gain via laboratory model based on dSPACE DS1104 digital control card.*

Key Words: ***Optimization/Model Reference Adaptive System/PI controller/Speed identification/Induction motor/Sensorless control***

1. INTRODUCTION

The indirect vector control of an induction motor requires precise speed information, therefore, a speed sensor, such as a resolver and encoder, is usually adhered to the shaft of the motor to measure the motor speed. However, a speed sensor increases the cost and requires a connection line between the control system and the motor, thereby preventing the stable operation of the control system due to interference from the signal line. Furthermore, an exact servo control performance is sometimes required in an operating environment where the attachment of a speed sensor is impossible. Accordingly, sensorless vector control that can precisely control an induction motor without a speed sensor has become an important research topic, resulting in the development of various speed estimation algorithms and sensorless control methods [1]. In an ideal sensorless drive, speed information and control is provided with an accuracy of 0.5% or better, from zero speed to the highest speed, for all operating conditions and independent of saturation levels and parameter variations [2]. Since a pure integration is generally needed in these observers, the speed estimation does no work well at low speeds. Therefore, these algorithms are, to a certain degree, machine parameter dependent [3]. In practical applications achieved accuracy of speed estimation using Model Reference Adaptive System (MRAS) to certain level depends on motor parameters variations [1, 2] and tuning quality of applied proportional integral controller (PI) [4]. For tuning of PI controller in MRAS scheme evolutionary optimization algorithms could be used successfully [5]. In this paper will be shown that gained speed estimation depends of applied optimization criteria and used optimization algorithms.

2. THEORY AND APPLIED TECHNIQUES

In this chapter will be given brief overview of theoretical base-ground and applied techniques that are used in this paper for solving problem of speed estimation.

2.1. Model Reference Adaptive System

Adaptive control has emerged as a potential solution for implementing high performance control systems, especially when dynamic characteristics of a plant are unknown, or have large and unpredictable variations. The MRAS achieves robust and high performance because of the presence of a reference model, which specifies the desired performance [6]. In a MRAS system, some state variables x_d, x_q (e.g. rotor flux-linkage components, Ψ_{rd}, Ψ_{rq} or back electro magnetic force component e_d, e_q) of the induction machine (witch are obtained by using measured quantities e.g. stator voltages and currents) are estimated in a reference model and are then compared with state variables x^*_d, x^*_q estimated by using an adaptive model. The difference between these state variables is then used in adaptation mechanism, witch outputs the estimated value of the rotor speed ω^*_r and adjust the adaptive model until satisfactory performance is obtained [2]. Such a scheme is shown in figure 1.

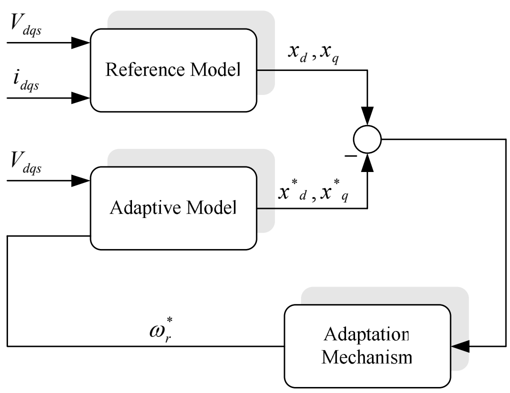

Figure 1. *Model Reference Adaptive System*

In a voltage source inverter fed drive, it is not necessary to monitor the stator voltage, since it is possible to reconstruct them by using inverter switching states and the monitored value of the d.c. link voltage.

In this paper is used MRAS scheme in witch state variables are rotor flux-linkage components Ψ_{rd}, Ψ_{rq} in stator reference frame. The expressions for the rotor flux linkage in the stationary reference frame can be obtained by using the stator voltage equations of the induction machine:

$$\psi_{rd} = \frac{L_r}{L_m}\left[\int (u_{sd} - R_s i_{sd})dt - L_s^{'} i_{sd}\right], \quad (1)$$

$$\psi_{rq} = \frac{L_r}{L_m}\left[\int (u_{sq} - R_s i_{sq})dt - L_s^{'} i_{sq}\right]. \quad (2)$$

These two equations represent a so-called stator voltage model, witch does not contain the rotor speed and is there for a reference model. Next two equations correspond to a current model, which contains the rotor speed, and therefore represent the adjustable (adaptive) model:

$$\psi_{rd}^{*} = \frac{1}{T_r}\int (L_m i_{sd} - \psi_{rd}^{*} - \omega_r T_r \psi_{rq}^{*})dt \,, \quad (3)$$

$$\psi_{rq}^{*} = \frac{1}{T_r}\int (L_m i_{sq} - \psi_{rq}^{*} - \omega_r T_r \psi_{rd}^{*})dt \,. \quad (4)$$

The reference and adaptive model are used to estimate the rotor flux linkages and the angular difference of the outputs of the two estimators. As the speed tuning signal is used:

$$\varepsilon_{\omega} = \psi_{rq}\psi_{rd}^{*} - \psi_{rd}\psi_{rq}^{*} \,. \quad (5)$$

This tuning signal is the input to linear PI controller witch outputs the estimated rotor speed:

$$\omega_r^{*} = K_p \varepsilon_{\omega} + K_i \int \varepsilon_{\omega} dt \,. \quad (6)$$

Various MRAS scheme for speed estimation could be found in literature [1, 2].

2.2. Indirect vector control of induction motor

In literature [2] various indirect vector control scheme could be found. In this paper puls width modulation (PWM) voltage source inverter (VSI) fed vector control of induction motor is used. Vector control represents decoupled control of torque and flux of induction motor:

$$T_r \frac{d\psi_{rd}}{dt} + \psi_{rd} = M i_{sd} \,, \quad (7)$$

$$m = \frac{M}{L_r} i_{sq} \psi_{rd} \,. \quad (8)$$

In indirect vector control scheme there is no direct measurement of any electrical and magnetic variable. Position of rotor is measured via incremental encoder and slip is calculated [2]:

$$\omega_r = \frac{M}{T_r}\frac{i_{sq}}{\psi_{rd}} \,. \quad (9)$$

In indirect vector control scheme proposed in [2] and implemented in this paper six control loops could be found: current i_{sx}, i_{sy}, flux, torque, speed and position control loop. For each control loop PI controller is used. Tuning of these control loops is not considered in this paper.

2.3. Artificial intelligence optimization algorithms

The genetic algorithm (GA) [7] is a method for solving both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution. GA could be apply to solve a variety of optimization problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, nondifferentiable, stochastic, or highly nonlinear. The genetic algorithm uses three main types of operations at each step to create the next generation from the current population: selection, crossover and mutation.

Simulated annealing (SA) [8] is a method for solving unconstrained and bound-constrained optimization problems. The method models the physical process of heating a material and then slowly lowering the temperature to decrease defects, thus minimizing the system energy. At each iteration of the simulated annealing algorithm, a new point is randomly generated. The distance of the new point from the current point, or the extent of the search, is based on a probability distribution with a scale proportional to the temperature. The algorithm accepts all new points that lower the objective, but also, with a certain probability, points that raise the objective. By accepting points that raise the objective, the algorithm avoids being trapped in local minima, and is able to explore globally for more possible solutions. An annealing schedule is selected to systematically decrease the temperature as the algorithm proceeds. As the temperature decreases, the algorithm reduces the extent of its search to converge to a minimum.

Since its introduction by Kennedy and Eberhart in the mid-1990, Particle Swarm Optimization (PSO) [9] algorithms raised a considerable interest. Originating in an attempt to mimic simplified social behavior of animals moving in large groups (such are fish or birds), PSO is grown to be a successful global optimization technique, well fit for solving complex, multimodal problems. In addition, compared to other evolutionary techniques, most notably the Genetic Algorithm (GA), PSO is simple and elegant in concept, it has few parameters and it is easy to implement. PSO operates on a set of particles. Each particle is characterized by its position (*x*) and velocity (*v*). The position of each particle is a potential solution, and each particle is capable of memorizing the best position it ever achieved in the course of the optimization process (*p*). The swarm as a whole memorizes the best position ever achieved by any of its particles (*g*).

3. OPTIMIZATION OF PI CONTROLLER IN MRAS SCHEME

For optimization of PI controller in MRAS scheme via GA, PSO and SA, Matlab/Simulink model has been design. Realization is shown in figure 2.

Implementation of indirect vector control scheme in witch one is MRAS estimator applied is not considered in this paper.

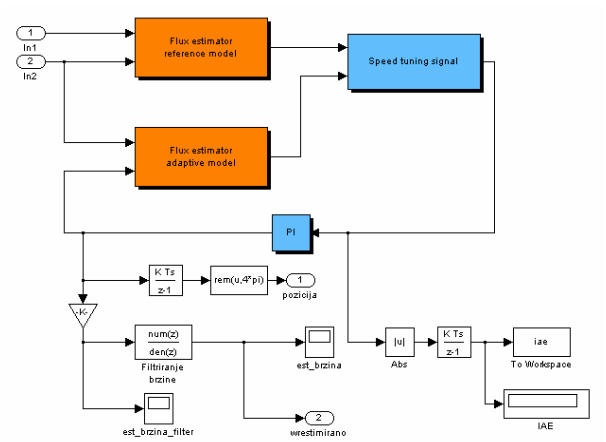

Figure 2. *MRAS scheme design in Simulink*

Important part of optimization process is definition of optimization criteria. Based on the result achieved in [4] some modifications to applied criteria has been done. Optimization criteria used in this paper must achieved two main goals. At first, must minimize integral absolute error (IAE) to achieved best tracking performance and secondly, must minimize parameters of PI controller K_p and K_i to reduce noise influence on estimated speed. The optimization criterion is stated as:

$$J_{opt} = C_1 \int |\varepsilon_\omega| dt + C_2 K_p + C_3 K_i . \quad (10)$$

Coefficients $C_{1\text{-}3}$ are used to scale physically different parameters to relative units and to normalize dimension of optimization criteria. Values are determent empirically. Values of parameters of used optimization algorithms wont be shown in this paper due to space saving. Default Matlab values for optimization algorithms parameters are used (except: GA generation 10, population 10; PSO iterations 10, particles 5; SA iterations 25). Table 1 gives overview of optimization results achieved via simulations in Matlab/Simulink.

Table1. *Optimization results*

Algorithm	K_p	K_i	J_{opt}
GA	525.7	16501	36.797
PSO	525	16503	36.792
SA	94	16886	34.163

From table 1 could be seen that minimal optimization criteria has been achieved via SA algorithm. Verification of simulation data will be carried out via laboratory model and comprehensive comparative experiments.

4. LABORATORY MODEL

Experiments were carried out on prototype model based on dSPACE DS1104 digital control card and two inductions motors. First, two poles machine is in drive mode and second, four poles, is load. Control algorithms are developed via ACE1104 system. DS1104 control card is based on PowerPC603e microprocessor. Drive machine is driven by current regulated voltage inverter based on IGBT (insulated gate bipolar transistor) Semikron SKM150GB123D modules. Maximal voltage for these modules is declared on 1200V, and maximum current is 50A. Laboratory model is shown in figure 3.

Figure 3. *Laboratory model*

Transfer of control signals generated by control card DS1104 is carried out by optical link. Optical link system consists of optical transmitter HFBR 1524, receivers HFBR 2524 and multy mode optical conductors OKE 1000 Agilent Technologies. LEM LA 55P sensors measure power supply currents with measuring ratio 1:1000. Measuring signals are amplified via LM741 and filtered by low pass filter with cut of frequency 2 kHz. For measuring of rotor angular speed on motor shaft was used optical encoder Omron E6C3 – CWZ3XH with 3600 impulses per revolution.

5. EXPERIMENTAL RESULTS

Based on theoretical background shown in chapter 2, simulation results shown in chapter 3 and laboratory model described in detail, chapter 4, comprehensive experiments have been conducted. Motor runs unloaded form zero to randomly given reference speed. Reference speed values of interest are: 0, 10, 25, 50 and 70 [rad/s]. Figures 4-6 give overview of measured and estimated speed for PI parameters gained with each algorithm. Figures 7, gives magnified speed-estimated signal for speed range 0 to 50 [rad/s] and figures 8, 9 on references speeds of 50 and 70 [rad/s]. From shown results could be seen that has been achieved relatively good estimation of speed in all three cases. Table 2 gives overview of mean absolute error on given speed references,

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |e_i|, \; e_i = \omega_{r(i)} - \omega_{r(i)}^{*} . \quad (11)$$

Table 2. *Mean absolute error values*

Algorithm	25 [rad/s]	50 [rad/s]	70 [rad/s]
GA	4.53%	1.11%	0.58%
PSO	4.56%	1.03%	0.56%
SA	4.53%	0.93%	0.34%

From table 2 easily could be seen that estimation error significantly increases as the reference speed decreases. Problem of speed estimation in low speed range stays present. Best performance is achieved via SA algorithm.

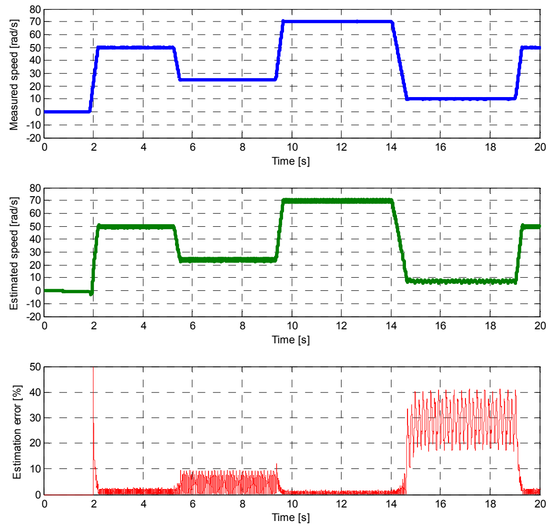

Figure 4. *Measured versus estimated speed for PI parameters gained via GA*

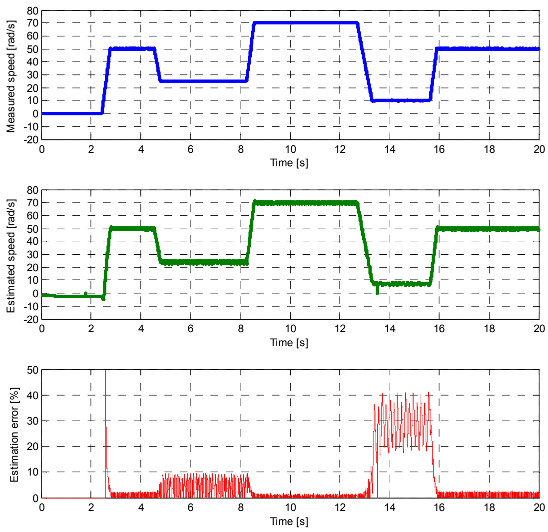

Figure 5. *Measured versus estimated speed for PI parameters gained via PSO*

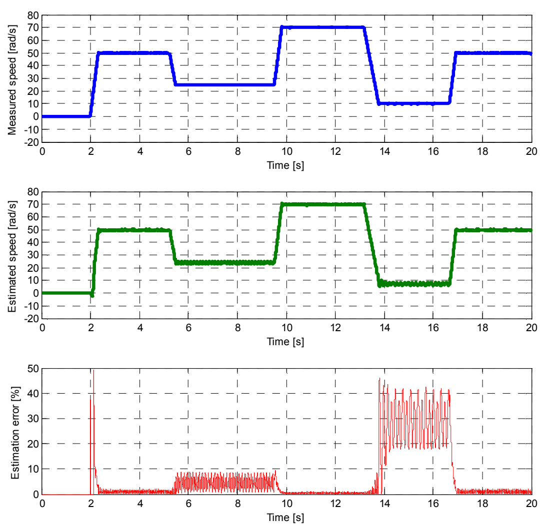

Figure 6. *Measured versus estimated speed for PI parameters gained via SA*

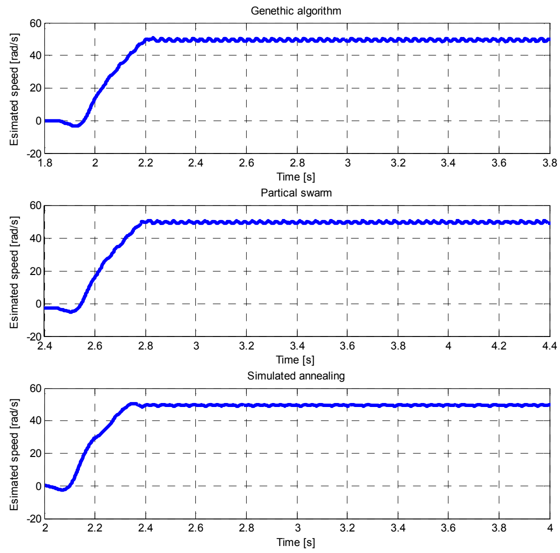

Figure 7. *Estimated speed for range 0-50 [rad/s]*

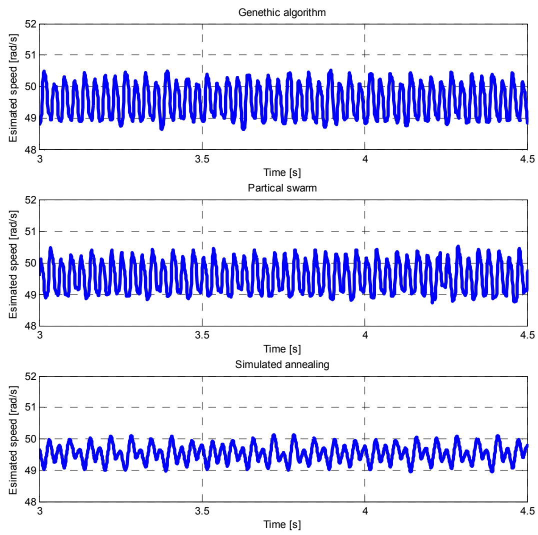

Figure 8. *Estimated speed for reference 50 [rad/s]*

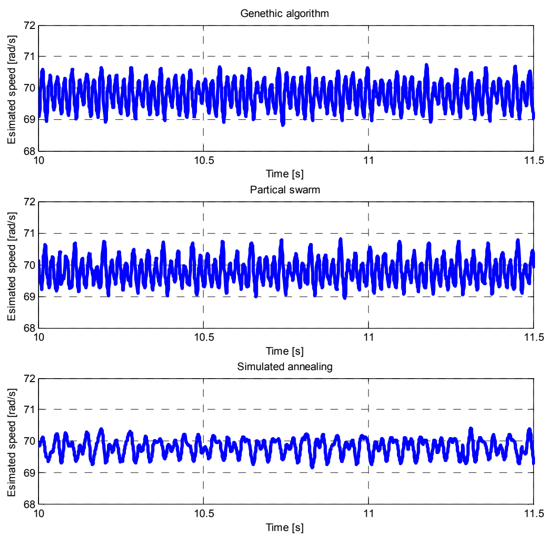

Figure 9. *Estimated speed for reference 70 [rad/s]*

6. CONCLUSION

Based on results shown in chapter 5 some general conclusion can be made. Artificial intelligence optimization algorithms can be successfully applied for problem of optimizing PI controller in MRAS scheme. Gained results depend on developed optimization criteria, used optimization algorithm and its parameters. MRAS scheme in practice is not absolutely robust to motor parameters variations (rotor and stator resistance could be increased for 100%) in general, R_s variation can result in poor performance at low speeds and L_s variation will affect the speed performance over the whole speed range. It is expectable that better results at zero reference can be gained if online estimation of stator resistance has been done. Problem of speed estimation in low speed range and at zero speed stays present. From figure 7 could be seen that quality of estimation on zero reference speed depends in some way to PI controller parameters, but it is not clear is it possible to gain good speed estimation on zero speed just by tuning parameters of PI controller. Is it possible to involve parameters variations in optimization criteria?

Ideal speed estimation with relative mean absolute error less than 0.5% can be achieved for some speed range but not at whole speed range, from zero to nominal speed. Quality of speed estimation achieved in this paper is satisfactory and can be applied in practical and commercial drives. Scheme is suitable for low-cost applications were speed information is not essential in whole nominal speed range.

Space for future scientific research exists. It is expectable that speed estimation of induction motor drives will be of interest for academic and industrial society. It seems that artificial intelligence (fuzzy logic, artificial neural networks and artificial optimization algorithms) will be more preset in solving problems related for applications of speed estimation.

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8. APPENDIX

Parameters of induction motors are: U_n=3x380VAC f_n=50Hz, T_r=90ms, T_e=10,2ms, R_s=5,25Ω, R_r=3,17Ω, L_s=0,2992H, L_r=0,285H, L_m=33,85mH, p=2, ω_{mb}=157rad/s.

Where are: U_n-main power supply, f_n-power supply frequency, u_{sd}, u_{sq} – dq stator voltage components, i_{sd}, i_{sq} – dq stator current components, Ψ_{rd}, Ψ_{rq} - rotor flux-linkage components, T_r-rotor time constant, T_e-equivalent time constant, R_s-stator resistance, R_r-rotor resistance, L_s-stator self induction, L_r-rotor self induction, L_m-mutual induction, p-number of poles, ω_{mb}-mechanical angular rotor speed, ω_r -.electrical angular rotor speed, M – mechanical torque, K_p – proportional controller gain, K_i – integral controller gain.

9. REFERENCES

[1] C.W Park, W.H Known, “*Simple and robust speed sensorless vector control of induction motor using stator current based MRAC*”, Electric Power Systems Research Vol. 71 pp. 257-266, May. 2004.

[2] Vas P.: *Sensorless Vector and Direct Torque Control,* Oxford University Press, 1998, ISBN13: 978-0-19-856465-2

[3] L.Zhen, L.Xu, “*Sensorless field orientation control of induction machine based on mutual MRAS scheme*”, IEEE Transactions of Industrial Electronics Vol.45 No.5, October 1998.

[4] Astrom K.J, Murray R.M: *Feedback Systems,* Princeton University Press, 2008, ISBN-13: 978-0-691-13576-2

[5] D.Matić, B.Dumnić, F.Kulić, V.Vasić.: *GA Optimization of PI Controller in MRAS Structure for Induction Motor Speed Estimation*, Proc. of IEEE NEUREL 2008 International Conference, Belgrade, Serbia.

[6] A.Paladugu, B.H.Chowdhury, “*Sensorless control of inverter-fed induction motor drives*”, Electric Power Systems Research Vol. 77 pp. 619-629, July. 2006.

[7] Mitchell M.: *An Introduction to Genetic Algorithms,* Massachusetts Institute of Technology, 1998, ISBN 0-262-13316-4 (HB)

[8] Salamon P., Sibani P., Frost R.: *Facts, Conjecture and Improvements of Simulated Annealing”*, Society for Industrial and Applied Mathematics, 2002

[9] Y.Shi, R.C.Eberhart: *Empirical study of particle swarm optimization*, Proc. of IEEE International Congress on Evolutionary Computation, vol. 3, 1999, pp. 101–106.