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NEURAL NETWORKS SOLUTIONS FOR AC MOTOR CONTROL

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Abstract – The paper presents alternative neural network (NN) solutions for the control of induction motor (IM) and permanent magnet synchronous motor (PMSM). Both NN methods, based on vector control, were compared with the classical respective method control for IM and PMSM. The proposed NN for IM is related with sensorless drives, based on a model reference adaptive system (MRAS) and the NN is designed to estimate the electrical rotor speed. As an alternative solution to classical vector control of PMSM, an inverse model neural controller with a simplified mechanism to reduce the speed offset during the control process is proposed. All the algorithms were experimentally tested in order to prove capabilities of NN to control the AC machines. The experimental tests have been developed around Motorola DSP56F805 fix-point processor to control the IM and respectively with DS1104 for PMSM control.

I. INTRODUCTION

The interest for sensorless induction motor (IM) drives has been constantly rising during the last years. The fact that the rotor speed is not measured, but estimated, has several important benefits, especially related to higher robustness, lower cost and lower sensitivity to noise. In this paper an on line trained neural network (NN) [1] is presented as an alternative solution to the classical model reference adaptive scheme (MRAS) [6], to estimate the rotor speed for a squirrel cage induction machine. The classical and respective the NN control algorithms, were experimentally tested using a Motorola DSP56F805 fix-point processor.
The high performance control of permanent magnet synchronous machine (PMSM) for industrial applications has received also a wide interest lately due to the recent achievements in high-energy permanent magnet materials [3]. Using the good learning ability and the high robustness of the NN an inverse control for PMSM [2], it is presented as an alternative solution for classical vector control. The experimental tests for the classical vector control and for the inverse neural control of PMSM were obtained using a real-time DS1104 system.

A. Sensorless technique based on model reference adaptive scheme (MRASPI)

The block diagram of the sensorless direct rotor field oriented control (DFOC) of induction motor using the MRAS technique [6] is presented in Fig. 1. Two flux estimators are used the first is a VI estimator as reference model, and the second is an estimator as adaptive model, designed with the following equations:

$$\frac{\mathrm{d}\overline{\boldsymbol{\psi}}_r^{vi}}{\mathrm{d}t} = \frac{L_r}{L_m}\left(\overline{\boldsymbol{v}}_s - R_s\,\overline{\boldsymbol{i}}_s - \sigma L_s\,\frac{\mathrm{d}\overline{\boldsymbol{i}}_s}{\mathrm{d}t}\right) \tag{1}$$

$$\frac{\mathrm{d}\overline{\boldsymbol{\psi}}_r^{i\omega}}{\mathrm{d}t} = -\frac{1}{T_r}\overline{\boldsymbol{\psi}}_r^{i\omega} + \frac{L_m}{T_r}\overline{\boldsymbol{i}}_s + j\omega_r\,\overline{\boldsymbol{\psi}}_r^{i\omega} \tag{2}$$

The classical method to estimate the electrical rotor speed (MRASPI) is deduced according with the Popov's hyperstability theorem [5]. The adaptation mechanism is based on the error signal, between the rotor flux components.

$$\varepsilon_\omega = \mathrm{Im}\left(\overline{\psi}_r^{vi}\overline{\psi}_r^{i\omega}\right) = \psi_{rq}^{vi}\psi_{rd}^{i\omega} - \psi_{rd}^{vi}\psi_{rq}^{i\omega} \tag{3}$$

This tuning signal is the input of a proportional integral element, which outputs the estimated rotor speed:

$$\hat{\omega}_r = \left(K_p + \frac{K_I}{\mathrm{s}}\right)\varepsilon_\omega \tag{4}$$

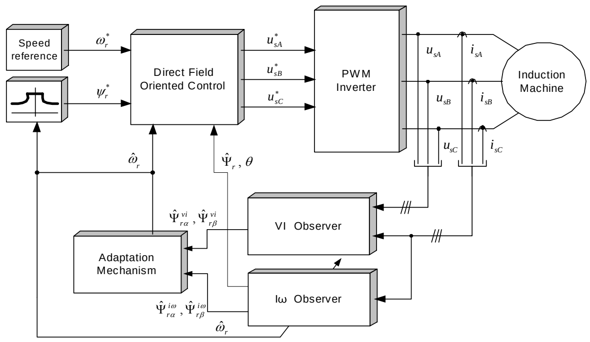

Fig. 1. MRAS based DFOC scheme

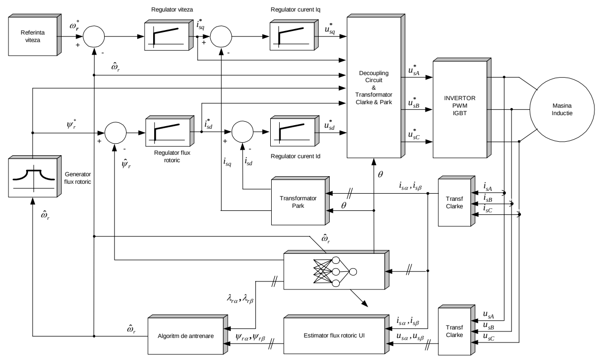

Fig.2. Neural network sensorless control of IM

B. Neural Network based method to estimate the electrical rotor speed (MRASNN)

The adaptive $I\omega$ flux observer can be designed like a simple neural network, if the discrete form of (2) is used:

$$\overline{\psi}_r^{i\omega}(\mathrm{k}) = \overline{\psi}_r^{i\omega}(\mathrm{k}-1) + \left(w_1 x_1 + w_2 x_2 + w_3 x_3\right) \tag{5}$$

where:

$$w_1 = -h/T_r, w_2 = h\omega_r, w_3 = hL_m/T_r \tag{6}$$

Using an on-line back-propagation algorithm with momentum term, a two layer neural network as can be seen from the Fig. 3, is supervised trained to minimize the error between the fluxes generated from the VI estimator (desired) and respectively from the NN the $I\omega$ estimator. The weights of the neural network are functions of the electrical parameters or electrical speed of IM as (6) suggests.

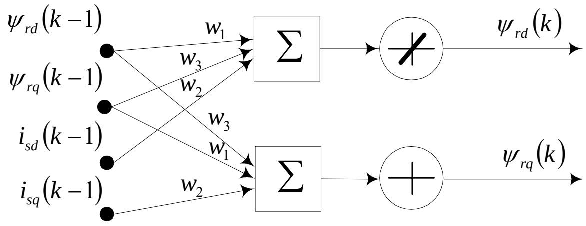

Fig. 3. Neural network architecture for IM control

The neural network has two neurons, with three inputs each (the stator currents and the rotor fluxes), and two outputs (the estimated rotor fluxes):

$$x_1 = \overline{\psi}_r^{i\omega}(\mathrm{k}-1), x_2 = j\overline{\psi}_r^{i\omega}(\mathrm{k}-1), x_3 = \overline{\mathrm{i}_s}(\mathrm{k}-1) \tag{7}$$

The electrical speed is adaptively computed as a weight of the neural network using the on-line back propagation algorithm, and afterwards is used to drive the induction motor:

$$\hat{\omega}_r(\mathrm{k}) = \hat{\omega}_r(\mathrm{k}-1) - \frac{\eta}{h}\delta\, x_2 + \frac{\alpha}{h}\Delta w_2(\mathrm{k}-1) \tag{8}$$

where: η is the learning rate of the neural network, α is the momentum term coefficient, h is the sampling time, and:

$$\delta = \left(\overline{\psi}_r^{i\omega}(\mathrm{k}) - \overline{\psi}_r^{vi}(\mathrm{k})\right)^{\mathrm{T}} \tag{9}$$

The algorithm described above is applied in this paper for a sensorless direct field oriented control of induction motor.

III. EXPERIMENTAL RESULTS WITH IM

The experimental tests were performed with a 2kW induction motor, controlled by Motorola DSP56F805 based board. The DSP56F805 is a 16 bits fix-point processor, and in order to control the induction machine a normalised Q15 mathematical model has to be derived. Considering the maximum values for stator voltage, stator current and electrical speed as base quantities all the other quantities can be further obtained. The switching frequency of the PWM inverter was set to 5 kHz and the test were performed with no load.

The voltage references in synchronous frame are obtained from the digital current controllers and as is known in order to obtain high dynamical performances the synchronous stator voltages have to be decoupled [6]. In the present paper a method to compensate the invertor dead time is also considered for the stationary reference stator voltages [7]. Another aspect, which needs special attention, is the implementation of the VI rotor flux estimator, because of the open loop dc integration problem and the zero speed operation [8].

The proposed neural network scheme for sensorless induction motor control MRASNN is experimentally tested in this paper for a direct rotor field oriented scheme and the results are compared with a classical MRASPI scheme. The tests were performed at low speeds below 500 rpm in order to demonstrate the effectiveness of the NN based scheme. Similar speed profiles were created for both scheme, reversion from 500 rpm to – 500 rpm and tests at minimum stable speed.

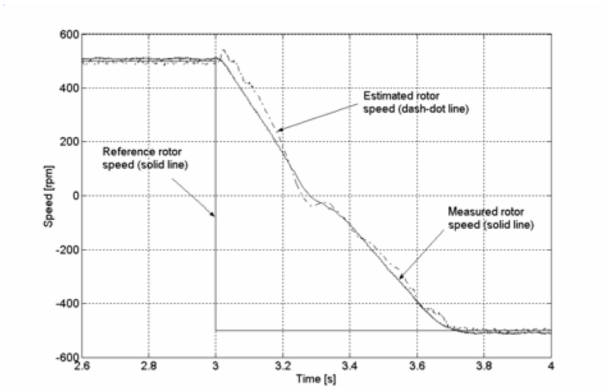

Fig. 4. Speed reference profile from 500 rpm to -500 rpm for MRASPI

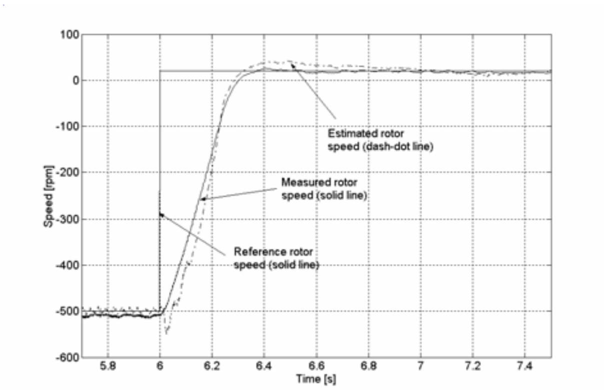

Fig. 5. Speed reference profile from –500 rpm to 20 rpm for MRASPI

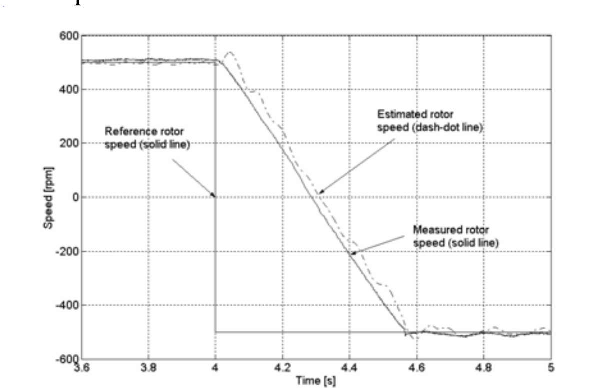

Fig. 6. Speed reference profile from 500 rpm to –500 rpm for MRASNN

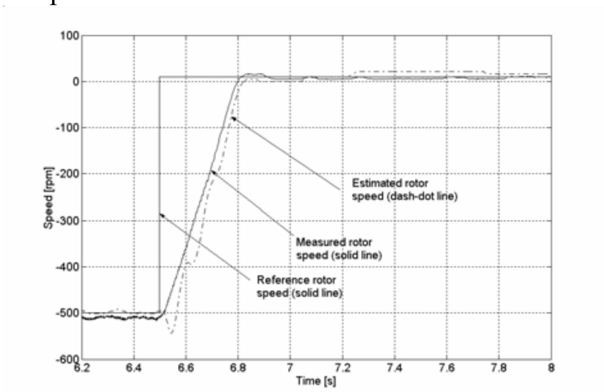

Fig. 7. Speed reference profile from –500 rpm to 10 rpm for MRASNN

For the MRASPI the minimum long time stable speed were obtained at 20 rpm, and for the MRASNN the minimum was settled at 10 rpm, as Fig. 5 and respectively Fig. 7 shows. The dynamical performances, the rising time for the MRASNN (0.56 s) is better than for the classical MRASPI (0.71 s). The performances of the MRAS based schemes can be improved if the rotor time constants variation is taking into the consideration, because of the $I\omega$ estimator. The MRASNN scheme can be improved if the NN will be fully trained for the remaining elements of the weighting vector, because w_1 is inverse proportional with T_1. This method it is not used into the present paper and remains a possible research direction.

IV. NEURAL NETWORK SOLUTION FOR PMSM

A. Vector Control of PMSM (PMSMPI)

The classical vector control technique is used in order to obtain high torque sensitivity of the PMSM through decoupling the quadrate axis – axis q and direct axis – axis d components of the stator currents formulated in the synchronous rotating reference frame [6]. In order to control the PMSM a PI speed controller is designed and synchronous PI current regulators were used. The reference current on axis d is set to zero and the speed is obtained from the rotor position available from an incremental encoder.

B. Neural Network Inverse Control of PMSM (PMSMNN)

The mathematical model of PMSM is described in [6] and it is not necessary to be available for the NN vector control. However it is possible to obtain the analytically inverse dynamic of the PMSM after some calculations starting from the differential equations of the mathematical model:

$$i_q(\mathrm{k}) = Ai_q(\mathrm{k}-1) + \frac{B}{e}\left[\omega_r(\mathrm{k}+1) - \left(a - \frac{eC}{B}\right)\omega_r(k)\right] - \frac{B}{e}\left[b\omega_r(\mathrm{k}-1) + c\omega_r^2(\mathrm{k}) + d\omega_r^2(\mathrm{k}-1) + f\right] \quad (10)$$

where *A, B, C, a, b, c, d, f* are constants and depends by machine parameters and sample time [2]. The purpose of the NN is to map the nonlinear relationship between the (q) axis current and the rotor speed. The proposed NN is presented in Fig. 9, and contains three hidden and one output neurons, with log-sigmoid activation functions.

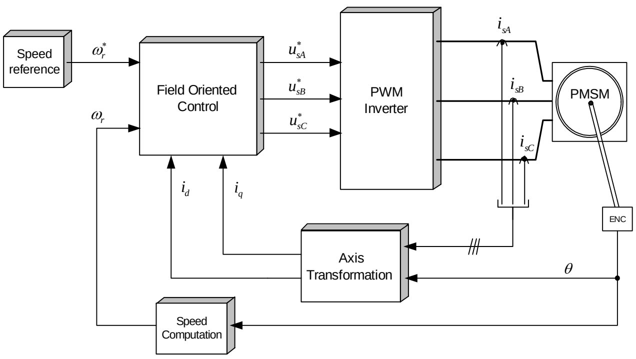

Fig. 8. Field Oriented Control for PMSM

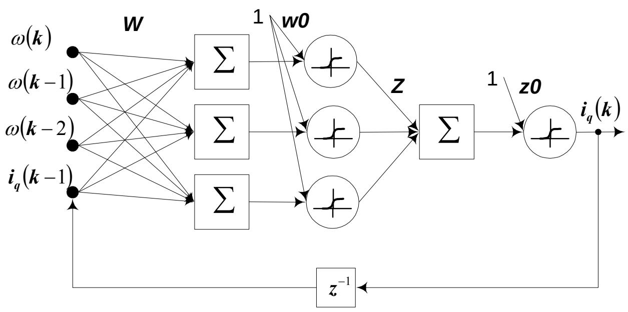

Fig. 9. Neural Network architecture for PMSMNN

The NN inputs are the rotor speed at the present and previous two samples intervals and respectively the previous i_q current sample. The corresponding output of the NN is the present current sample of the q-axis current. The NN has to be trained off-line in order to obtain the initial values for the weights matrices ***W*** and ***Z***, and for the bias values ***w0*** and ***z0***. The training data were obtained from the open loop control of the PMSM, generating random values for the i_q current [3]. The data set is then normalised and the NN is trained using the Levenberg-Marquardt back propagation algorithm, which quickly converge to the prescribed error. It is known that the NN based just on the initial weights and without a suitable method to update the weights and bias through the on-line back propagation, it is an unacceptable solution for high performance drives. The inconvenience occurs due to the fact that the NN acts like a proportional regulator, which introduces an offset between the imposed and realized rotor speed. In order to overcome this situation the NN has to be online trained, but this task is evidently difficult to be accomplished due to the facts that the desired signals are not available in real time drives, and from highly computational reasons.

In the present paper a simplified method to correct the NN dynamics is considered based on the fact that an integral component has to be added to the output of the NN. The proposed structure is presented in Fig. 10.

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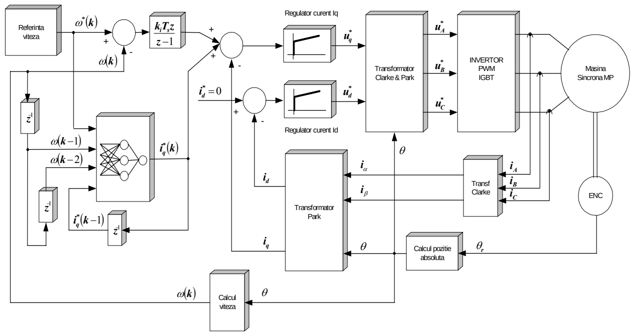

Fig. 10. Neural Network control of PMSM

V. EXPERIMENTAL RESULTS WITH PMSM

The DS1104 system is used to control the PMSM and combines the functionality of a TMS fix-point DSP with powerful MPC8240 processor, for hardware related features and the Matlab/Simulink RTI for easy software development. The control algorithm is developed under Simulink environment using C in conjunction with s-functions. Different quantities can be visualized in real-time and saved from the experimental stand using the ControlDesk application. Field oriented control requires information about the rotor position and speed, which is obtained from an incremental encoder, which provides 2500 lines/rpm and numerical computation. It is well known that at start time for correct operation the relative position have to be adjusted accordingly to avoid the reset of the first index. The correction algorithm compute the absolute position as can be seen in Fig. 13, either for parasite index signals, which means the reset of the counter. The rotor speed is obtained from absolute position using a digital low pass filter and (11).

$$\omega_r = \frac{1}{h}\left(\sin(\theta_a(\mathrm{k}))\cos(\theta_a(\mathrm{k}-1)) - \sin(\theta_a(\mathrm{k}-1))\cos(\theta_a(\mathrm{k}))\right) \tag{11}$$

The performances of the PMSMPI and PMSMNN schemes were compared for speed profile from 250 rpm to 500 rpm and for reversion from 500 rpm to – 500 rpm, as Fig. 11, 12 shows. The results show the abilities of the NN to generalise and to control the PMSM in real-time environments. Special attention has to be accorded to the training process in order to obtain the initial values of the NN weights and biases. The training data was generated using open loop scheme for PMSM for a speed range ± 314 rad/s, which means ± 750 rpm, and contains 80,000 pairs of input-output data vectors. The inputs of the NN are normalised, for better numerical representation due to the nature of the log-sigmoidal activation functions of the neurons between $[0.1 \div 0.9]$. The switching frequency of the PWM inverter was set to 5 kHz and the schemes were tested with load (Fig. 14). As for IM control a method to compensate the inverter dead time is also considered for the stationary reference stator voltages [7].

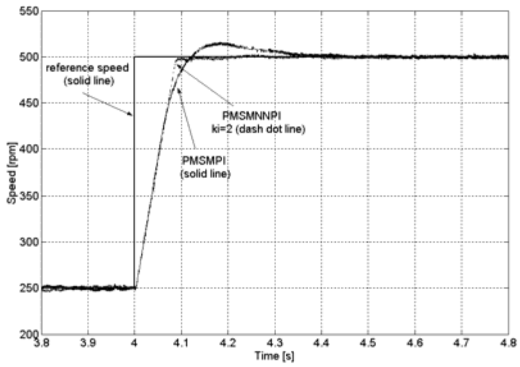

Fig. 11. Speed profile detail of PMSM control from 250 to 500 rpm

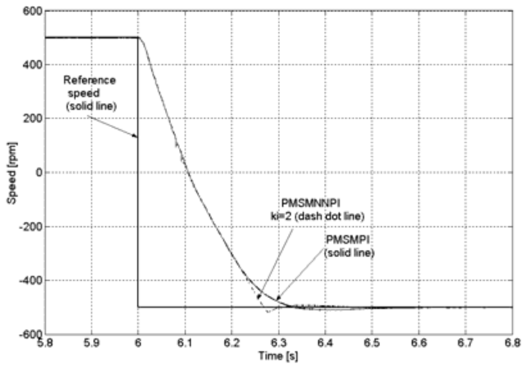

Fig. 12. Speed profile detail of PMSM control from 500 to -500 rpm

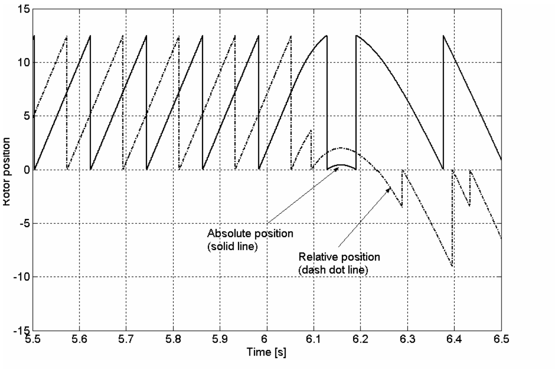

Fig.13. Relative/absolute pos. during the reversion

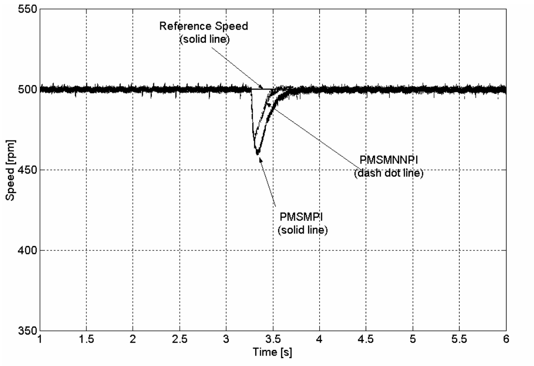

Fig. 14. Rotor speed response to load torque

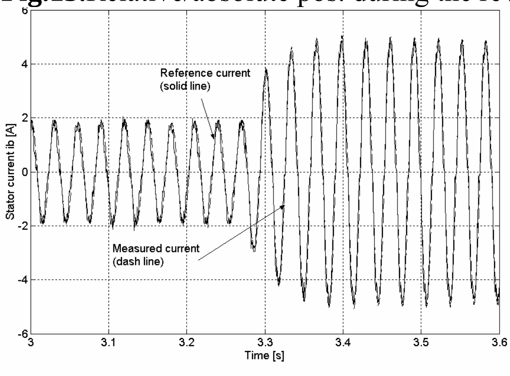

Fig. 15. Stator current response to load torque with PMSMPI

IM data	PMSM data
Rated Output Power: 2 kW	Rated Torque: 7 Nm
Rated Torque: 14 Nm	Rated Current: 11.7 A
Rated Voltage: 220 V	Pole Pairs: 4
Rated Frequency: 50 Hz	Rated Speed: 750 rpm
Rated Speed: 1350 rpm	Rated Frequency: 50 Hz
Stator Resistance: 2.71 Ω	Resistance: 0.33 Ω
Rotor Resistance: 3.73 Ω	Inductivities: 11.2 mH
Stator Inductivities: 0.284 H	Inertia: 19e-4 kgm²
Mutual Inductivity: 0.269 H	
Inertia: 0.05 kgm²	

VI. CONCLUSIONS

This paper presents alternative neural network based solutions to AC motor drives. There are presented two neural networks based schemes for sensorless induction motor control, MRASNN and respectively for permanent magnet synchronous motor control, PMSMNN. The proposed NN solutions were experimentally compared with the respective classical methods, MRASPI and PMSMPI in order to validate the effectiveness of the algorithms. The presented results show that the neural networks offer alternative solutions to classical control schemes with comparable performances. In the presented schemes the neural networks structures are relatively simple and the required computational effort it is not higher than in the other classical schemes. Even more than that, with presented PMSMNN scheme the on-line training of the neural network is avoided and the computational effort remains at a reasonable level with good dynamical performances.

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