Hybrid Artificial Neural Network for Induction Motor Parameter Estimation

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ABSTRACT

Three-phase induction motor electric parameter estimation has been widely used to improve induction motor control performance. A precise match between electrical parameter values and estimated ones is imperative. A value deviation can make induction motor misbehave, which can cause motor overheating even instability. Parameter estimation can be achieved on-line or off-line way with a large number of methods developed to calculate magnetic flux, motor speed, rotor resistance and rotor time constant. These methods include observers, adaptive systems, spectral analysis and artificial intelligence such as neural networks and fuzzy logic. This paper is focused on a hybrid neural network proposed to obtain rotor resistance and speed values, using Texas Instrument development tools to improve a sensorless vector control scheme an improve motor performance.

1. INTRODUCTION

Industrial field requires more accuracy and control in their processes. For that reason higher-performance Adjustable Speed Drives (ASD) are needed, to control three-phase Induction Motors (IMs) in order to accomplish standards of precision processes in their applications. IMs are actuality the most employed electric motor in industry due to their advantages such as robustness, quiet operation, low cost, maintain-free and efficiency. Thanks to use different electrical parameter identification techniques such as observers and estimators based on artificial intelligence, IM drives are now capable of controlling them even at low operation frequencies, different temperature levels and load changes without need of an encoder.

Field Oriented Control scheme (FOC) is one the most used methods to control IMs. Which can also be sensorless implemented in order to estimate IM rotor speed (ω_r). But sensorless FOC is strongly dependent on rotor resistance (R_r) value and if the estimation of this parameter mismatches with the real value, motor operation can be compromised. This value is modified by external factors such as IM aging, operation frequency or working temperature increase as explained in [1]. Digital Signal Processors (DSPs), Microcontrollers (μCs) and Digital Signal Controllers (DSCs), Microprocessors (μPs) and Artificial Intelligence (AI) have resulted very helpful in this area.

Thus, numerous researches using artificial neural networks (ANNs) and fuzzy control have been presented recently. In order to obtain autonomous systems capable of learning and develop preventive action based on experience, ANNs have been used in control problems and identification tasks. ASD control issues have allowed that ANNs improve motor control schemes.

In this paper, a new proposed scheme to estimate the induction motor R_r and its ω_r in an on-line way with a Hybrid Artificial Neural Network (HANN) is presented, implemented on a DSC (Piccolo F28035) combining two ANN structures. Which allows the driver to be compensated from R_r variations and adjust the FOC sensorless scheme. Section II presents the HANN equations that are implemented in the DSC. Section III presents a test bench and instruments used to implement a sensorless FOC controller, Section IV presents the results obtained from the implementation. Finally, in the last section of this research the conclusions are discussed.

2. ANN STRUCTURE SELECTION

Actually, numerous ANN schemes have been reported, there is not a rule to pick up the correct structure only experience and knowledge of the problem can help to select an option to solve a specific problem. The main idea that motivates this work is to prove notoriously that, general FOC scheme performance to drive IMs, can be improved with this new ANN proposed. In [2], there is a survey, where different ANN structures and training algorithms are described and analysed. In this structure compilation, two ANNs are selected and discussed for their effectiveness and simplicity to be implemented, one is an Adaptive Linear Neuron (ADALINE) structure presented in [3] and [4] and the other one is a Cerebellar Model Articulation Controller (CMAC) reported in [5].

They are used as estimators and observers to estimate IM magnetic flux (λ), ω_r, R_r or finally rotor time constant (T_r). In some cases ANN structures are also used as controllers. A common response from a general sensorless FOC is shown in figure 1. It is visible how vector control speed tracking is affected by the working frequency. Velocity estimation can´t be achieved at low revolution per minute (RPMs) due to R_r changes.

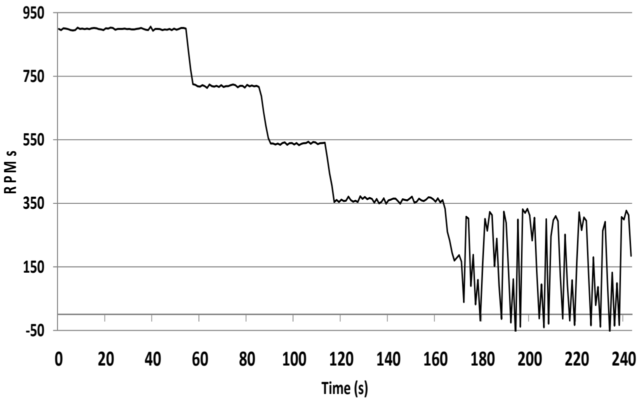

Figure 1 - Structure of the proposed ANN to estimate IM speed and rotor resistance.

List of terms used in equations.

$\vec{V_s} = \begin{bmatrix} V_{ds} \\ V_{qs} \end{bmatrix}$: d-q axes stator voltages.

i_{ds}, i_{qs} : d-q axes stator currents.

$\vec{\phi}_r = \begin{bmatrix} \phi_{dr} \\ \phi_{qr} \end{bmatrix}$: d-q axes voltage model rotor fluxes in stationary reference frame.

$\vec{\lambda_r} = \begin{bmatrix} \lambda_{dr} \\ \lambda_{qr} \end{bmatrix}$: d-q axes current model rotor fluxes in stationary reference frame.

$\overrightarrow{\lambda_r^{nm}} = \begin{bmatrix} \lambda_{dr}^{nm} \\ \lambda_{qr}^{nm} \end{bmatrix}$: d-q axes estimate neural network model.

$\sigma = 1 - \frac{L_m^2}{L_s L_r}$: Leakage coefficient.

ω_r : Electrical rotor angular velocity.

$T_r = \frac{L_r}{R_r}$: Rotor time constant.

3. HYBRID ARTIFICIAL NEURAL NETWORK DESCRIPTION

It order to implement this HANN is necessary to consider current model given by (1), voltage model by (2) is also required to adjust the weights, these equations are shown in the following lines and explained in [6].

$$\vec{\lambda_r} = \left(\frac{-1}{T_r} I + \omega_r J \right) \vec{\lambda_r} + \frac{L_m}{T_r} \vec{i_s} \qquad (1)$$

$$\vec{\phi_r} = \frac{L_r}{L_m} \left(\vec{V_s} - R_s \vec{i_s} - \sigma L_s \vec{i_s} \right) \qquad (2)$$

Where:

$$I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad J = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}, \quad \vec{i_s} = \begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix}$$

Current model that is given by (1) is considered to obtain HANN equations.

The discrete data model of (3) can also be expressed as:

$$\overrightarrow{\lambda_r^{nm}}(k) = (W_1 I + W_2 J) \overrightarrow{\lambda_r^{nm}}(k-1) + W_3 \vec{i_s}(k-1) \qquad (3)$$

Considering:

$$W_1 = 1 - \frac{T_s}{T_r}; \quad W_2 = \omega_r T_s; \quad W_3 = \frac{L_m}{T_r} T_s$$

And

$$X_1 = I \overrightarrow{\lambda_r^{nm}}(k-1) = \begin{bmatrix} \lambda_{dr}^{nm}(k-1) \\ \lambda_{qr}^{nm}(k-1) \end{bmatrix}$$

$$X_2 = J \overrightarrow{\lambda_r^{nm}}(k-1) = \begin{bmatrix} -\lambda_{dr}^{nm}(k-1) \\ \lambda_{qr}^{nm}(k-1) \end{bmatrix}$$

$$X_3 = I \vec{i_s}(k-1) = \begin{bmatrix} i_{ds}(k-1) \\ i_{qs}(k-1) \end{bmatrix}$$

It is possible to rewrite the equation (1) as (4):

$$\overrightarrow{\lambda_r^{nm}}(k) = W_1 X_1 + W_2 X_2 + W_3 X_3 \qquad (4)$$

ADALINE structure is represented by (4), as it is shown in figure 2.

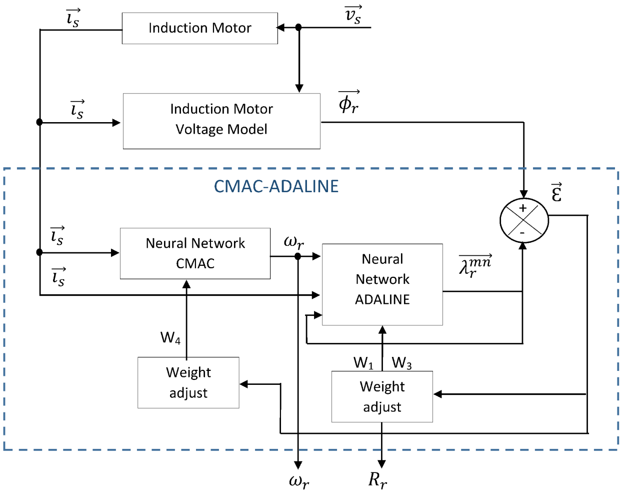

Figure 2 - Structure of the proposed HANN to estimate IM speed and rotor resistance.

It is important to consider error between rotor flux, voltage model flux and the HANN output to obtain weights W_1 and W_3. Thus, weight W_2 is result of the speed value at the instant T:

$$\vec{\varepsilon}(k) = \overrightarrow{\phi_r}(k) - \overrightarrow{\lambda_r^{nm}}(k) \tag{5}$$

Wight are adjusted, starting from the fact of minimizing the error in the energy equation as seen in (6).

$$E = \frac{1}{2}\vec{\varepsilon}^2(k) = \frac{1}{2}\left\{\overrightarrow{\phi_r}(k) - \overrightarrow{\lambda_r^{nm}}(k)\right\}^2 \tag{6}$$

When equation (6) is partially differentiated, weight variation is obtained by equation (7).

$$\Delta W_n(k) \propto -\frac{\partial E}{\partial W_n} = -\frac{\partial E}{\partial \overrightarrow{\lambda_r^{nm}}(k)} \frac{\partial \overrightarrow{\lambda_r^{nm}}(k)}{\partial W_n} = -\vec{\delta} X_n \tag{7}$$

A training coefficient (η) and another coefficient (α) are added to determine the effect of past weight changes, besides considering the effect that previous weight has in the new value of itself. [6]:

$$W_1(k) = W_1(k-1) - \eta\vec{\delta} X_1 + \alpha \Delta W_1(k-1) \tag{8}$$

$$W_3(k) = W_3(k-1) - \eta\vec{\delta} X_3 + \alpha \Delta W_3(k-1) \tag{9}$$

And rotor resistance can be found from either W_1 or W_3 using equations (10) or (11).

$$R_r = \frac{L_r W_3}{L_m T_s} \tag{10}$$

$$R_r = \frac{L_r (1 - W_1)}{T_s} \tag{11}$$

The CMAC network output (ω_r) is an input for the ADALINE structure, the same one used to adjust W_2. There is a fourth weight named W_4 in CMAC, this weight variation depends on the error, as shown in the following equation:

$$\Delta W_4(k) = \left(\overrightarrow{\phi_r}(k) - \overrightarrow{\lambda_r^{nm}}(k)\right)^T J \overrightarrow{\lambda_r^{nm}}(k-1)$$

And the weight W_4 value is calculated as follows:

$$W_4(k) = W_4(k-1) + \frac{\alpha}{M} \Delta W_4(k) \tag{12}$$

Where α and M represent a learning rate and the number of the activated association cell respectively. Finally, the estimated speed is obtained by combining equations above, the estimated rotor speed is represented as follows [7]:

$$\hat{\omega}_r(k) = \hat{\omega}_r(k-1) + \frac{\alpha}{M} \frac{\Delta W_4(k)}{T_s} \tag{13}$$

4. TEST BENCH AND IMPLEMENTATION FOR THE SPEED DRIVE

The testbench (figure 3) is composed by: the dynamic load, which is consist of a Direct Current (DC) motor controlled by a servo amplifier in current mode that it is managed by a National Instrument Data Acquisition Card (DAQ) in order to command the desired torque. An induction motor, see table 1, that is coupled by means of a torque meter and finally the development kit TMDSHVMTRPFCKIT, which contains a control card with the Piccolo F28035 from Texas Instruments (TI). A detailed methodology for the implementation of the sensorless technique can be found in [8] also together with the Digital Motor Control (DMC) library from TI [9] allows a flexible interconnection between the provided structures and the independent target application.

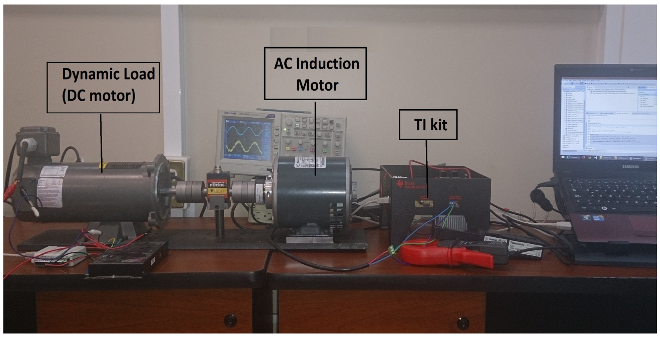

Figure 3 – Testbench and TI TMDSHVMTRPFCKIT.

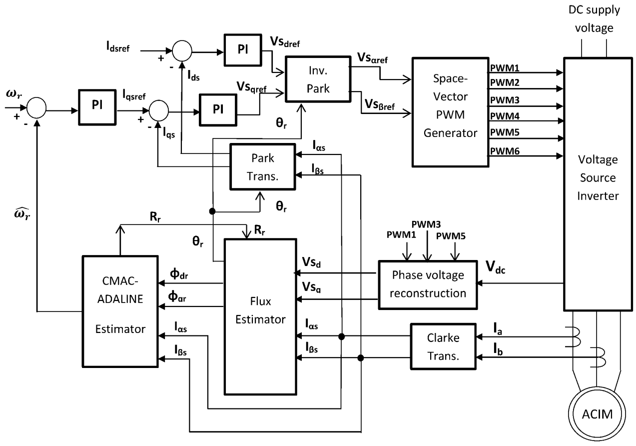

Figure 4 – HANN estimator block develop for DMC library

The modules shown in the figure 4, are provided in the Digital Motion Control (DMC) Library by TI, which contains several structures for data acquisition, Space Vector Pulse Wide Modulation (SVPWM) techniques, Digital Signal Processing (DSP) and control modules like PID controller, also provides efficient algorithms for the Park and Clark transformations. Some of the modules are listed below:

- Space Vector PWM Generator -> SVGEN_DQ
- Inverse Transform Park -> IPARK
- Park Transform -> PARK
- Clark Transform -> CLARKE
- PI Controller -> PI
- Flux Estimator -> ACI_FE
- Phase Voltage Reconstructor -> PHASE_VOLT

Another advantage of the DMC library is that can be fully customized and expanded by adding new structures, such as the proposed HANN based on the equations aforementioned. The HANN is structured similarly to the DMC library blocks for fast implementation and code reusability in IQ24 format. This approach provides a modular implementation as is shown in figure 4 of several high performance motor control techniques.

Table 1. Parameters induction motor.

¼ HP, 1725 rpm, 208-230 V, 3 phase, 4 poles, 60Hz
Stator Resistance R_s : 11.05 Ω
Stator Inductance L_s : 0.316423 H
Rotor Resistance R_r : 6.11 Ω
Rotor Inductance L_r : 0.316423 H
Mutual Inductance L_m : 0.293939 H

5. IMPLEMENTATION RESULTS

In this section the developed HANN algorithm is implemented and validated using the TMDSHVMTRPFCKIT, which already has a sensorless FOC embedded drive for an IM. The estimated variables by the HANN, are rotor speed and R_r. The variable, that is measured and observed, is rotor speed. The R_r is compared with IM manufacturer as shown in figure 5. In the same form, estimated speed (CMAC output) is observed in figure 6. For the experiment, a variable increasing and decreasing velocity profile was applied to the motor under load changes as it can be observed in figure 7. The DATALOG structure in the DMC library was used for data acquisition and transmitted through a standard universal asynchronous receiver-transmitter (UART) peripheral to an USB-to-Serial converter. The variables were processed with Visual C# and plotted with Excel. A detailed technical implementation of the hardware used is reported in [9], where the workstation used for motor load changes can be visualized. Table 1 shows the parameter of the used IM.

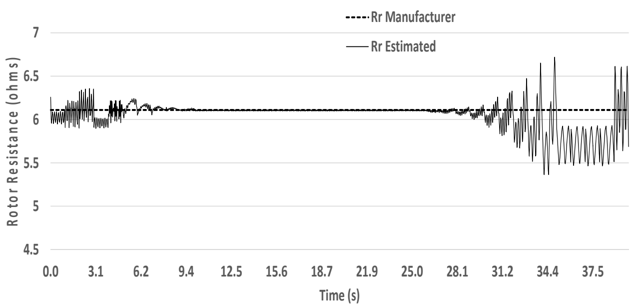

Figure 5 – Estimated Rr vs Desired Rr.

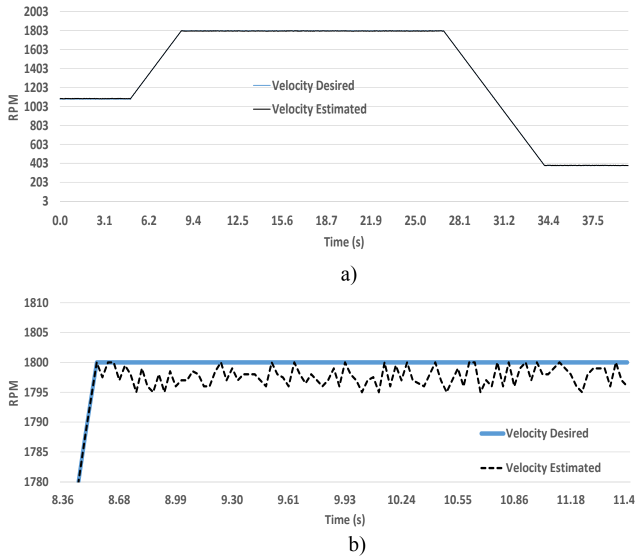

Figure 6 – a) Estimated ω_r vs Desired ω_r and b) Zoom in speed comparison

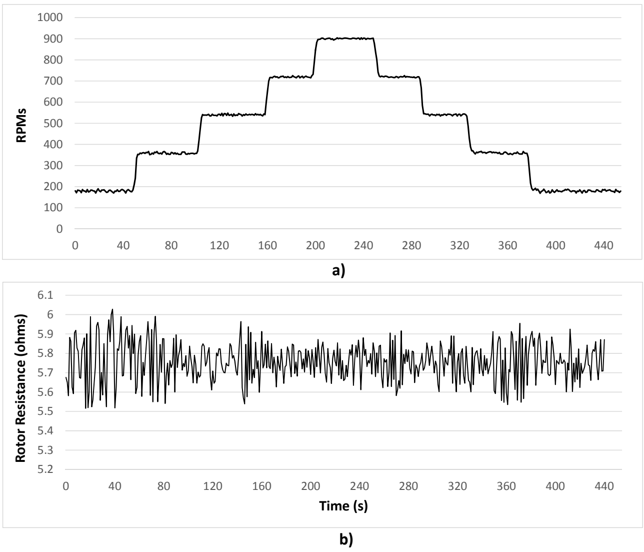

Figure 7 – a) Comparison between manufacturer motor resistance and estimated one, b) Speed change profile from 180 to 900 RPM with 1 N.m. load.

6. CONCLUSIONS

A hybrid neural network estimator is designed based on two neural network structures, to estimate rotor speed and resistance of an induction motor. This estimator adjusts its set of weights in order to update these two values, which improves FOC algorithm behavior. The HANN is implemented in the TI tool set TMDSHVMTRPFCKIT in a real-time application on a three-phase induction motor and it achieves speed and resistance tracking with a minimum error. Therefore, the implementation of this algorithm is simple, starting from DMC-library already-made control blocks, current and voltage model. It can be observed that the results are very satisfactory taking into motor was connected to a dynamic load with different torque perturbations, which was modified during test.

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