Rotor Flux Observer based Neuro-Fuzzy Techniques to Speed Vector Control of a Bearingless AC Motor

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***Abstract*— This study presents the problem of rotor flux orientation control of bearingless induction motor. The key of this solution is the estimation of rotor flux. This work applied an inference system using fuzzy logic and the neural networks with the MATLAB®. The Adaptive Neuro-Fuzzy Inference System (ANFIS) is based in an input-output model. ANFIS is used to tune the membership functions in fuzzy system and utilize the backpropagation learning algorithm. This system was applied to estimate the rotor flux and the magnetization current of the purpose of identifying bearingless induction motor angular speed. The hybrid estimator aims at compensating possible parametric variations of the machine caused by agents such as temperature or nucleus saturation. The simulated results showed good performance. The results demonstrated the feasibility of the proposed technique. The ANFIS estimator proposed will be embedded in the DSP TMS 3208F28335 in future works.**

I. Introduction

In recent years, there is an increasing interest in bearingless motors around the world. Principally in some industry sectors, such as oil extraction industry, the common problems of maintenance, reliability, efficiency and longtime life issues in conventional electrical machines are leading to the use of bearingless motors [1-2].

Bearingless induction motor is an integration of magnetic bearing with the function of a motor [3]. The Bearingless motors were designed to solve the reducing volume issue of conventional Induction Motor (IM) [5]. In these motors, rotor positioning and torque generation are realized through magnetic forces provoked by stator current control of the motor. So, in this sense, bearingless motors behave as a conventional IM [4].

Research on control of induction motors in recent decades have focused on the improvement of control schemes for field-oriented or vector control, to solve the problems presented by the use of sensors attached to or installed near the rotor [6]. The Flux estimation is an important part in induction machine control system. The flux information is needed in induction machine control for the purpose of synchronous angle and synchronous speed estimation, flux regulation and torque regulation.

Neural Networks (NN) and Fuzzy Logic (FL) are widely used in the areas of modelling, identification, diagnostics and control [9]. In [10] use ANN to reject the influence of speed detection on system stability and precision for a bearingless induction motor. In order to compensate the disadvantages of one system with the advantages of another system, several researchers tried to combine fuzzy systems with Neural Networks [7]. A Neuro-Fuzzy system is simply a Fuzzy inference system trained by a Neural Network-learning algorithm. The Adaptive Neuro-Fuzzy Inference System (ANFIS) [8] combines Fuzzy Logic and Artificial Neural Networks.

The vector control technique needs flux sensors to determine the exact value of the magnitude and of the position of the rotating flow [7]. This limitation was resolved with the flux estimator based on vector control of motor model using as reference the rotor flux vector requiring only the stator phase currents and speed mechanics [11].

ANFIS simultaneously estimates flux speed and magnetization current that defines the rotor flux position (after integrating flux speed) and rotor flux magnitude. The results simulated in the MATLAB® showed satisfactory to estimation of flux with ANFIS due the excellent stabilization of variation parameters of the motor.

II. Modeling of a Bearingless Induction Motor

A three phase, four poles, conventional squirrel cage IM, has its stator winding lodged in adjacent slots. The stator of the induction machine used has divided windings, as shown in Fig. 1.

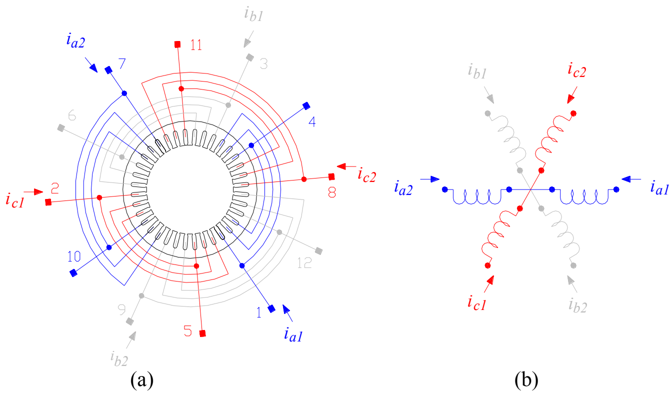


Figure 1. (a) Schematic distribution of stator coils and (b) circuit diagram.

A. The Flux Model

For the flux estimation or conventional estimator, is being used the vectorial model of conventional induction machine [13]. The applied model is described for the following equations:

$$\frac{di_{mR}(t)}{dt} = \frac{i_{sd}(t)}{T_R} - \frac{i_{mR}(t)}{T_R} \tag{1}$$

$$i_{mR}(t+h) = i_{mR}(t) + h.\frac{di_{mR}(t)}{dt} \tag{2}$$

$$\frac{d\rho(t)}{dt} = \omega_{mec}(t) + \frac{i_{sq}(t)}{T_R i_{mR}(t)} \tag{3}$$

$$\rho(t+h) = \rho(t) + h.\frac{d\rho(t)}{dt} \tag{4}$$

$$m_M(t) = k.i_{mR}(t)i_{sq}(t) \tag{5}$$

$$k = \frac{2}{3}(1-\sigma)L_S \tag{6}$$

where h is the integrative step, $i_{mR}(t)$ is the magnetizing current, $i_{Sd}(t)$ and $i_{Sq}(t)$ are the Park currents, $\rho(t)$ is the rotor flux position, $mM(t)$ is the electric torque, $\omega_{mec}(t)$ is the rotor mechanical speed, T_R is the rotor time constant, L_s is the stator inductance and σ is the leakage factor.

The use of conventional vector model of induction machines in the study of the bearingless induction machine with divided windings was only possible due to the similarity between their stators structures. Such similarities are equivalent on both models [5] allowing the implementation of the speed and radial positioning controllers.

B. Behavior of the Flux density

It was used a simulator based on the finite element method for acquiring flux density for a model of IM. Fig. 2 shows flux density distribution of the rotor to different current of each phase group.

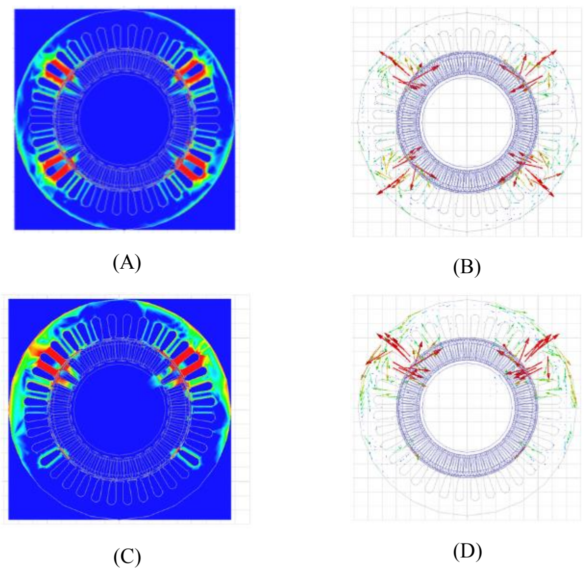


Figure 2. Behavior of the Flux density distribution of the Rotor.

The Fig. 2 (A) and (B) presents the rotor flux vector behavior to the centralized rotor positioning. Rotor magnetic field analysis was realized by means of Maxwell tensor method [12]. Fig. 2 (C) and (D) presents the rotor flux vector behavior to the decentralized rotor positioning. Current were unbalanced to fix the position of the rotor.

III. ANFIS

The chosen Neuro-Fuzzy system is used ANFIS (Adaptive Network-based Fuzzy Inference System) [8]. It adapts the values of inputs and outputs from the base of rules that establish all the input and output connections. Thus, it generates a robust base of rules that creates an Inference System Fuzzy in which contemplates all the possible inputs.

The Neuro-Fuzzy system can be analyzed as Fuzzy Inference, implemented under the architecture of the neural network. ANFIS structure based on the model Takagi-Sugeno first-class. A typical architecture of an ANFIS is as shown in Fig. 3.

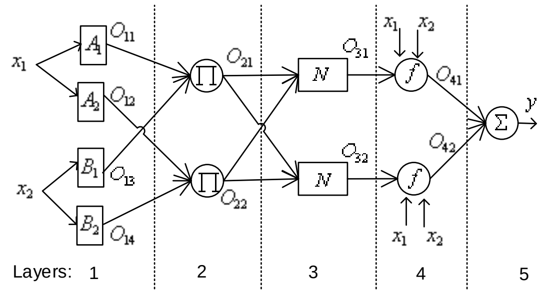


Figure 3. Basic structure of ANFIS.

Layers 1 – Every node i in this layer is a square node with a node function as:

$$O_{1,i} = \mu_{Ai}(x_1), i = 1,2. \quad O_{2,i} = \mu_{Bi}(x_2), i = 1,2. \tag{7}$$

where x is the input to node i, A_i or (B_i) is a linguistic label (such as "*smal*" or "*large*") associated with this node and μ_{Ai} and μ_{Bi} can adopt any fuzzy membership function(MF). Parameters in this layer are referred to as "premise parameters".

Layers 2 – Every node in this layer is a fixed node labeled as ∏, whose output in the product of all incoming signals:

$$O_{2,i} = w_i = \mu_{Ai}(x_1)\mu_{Bi}(x_2), i = 1,2. \tag{8}$$

Layers 3 – Every node in this layer is a fixed node labeled as N. The i node calculated the ratio of the rule's firing strength to sum of all rules firing strengths:

$$O_{3,i} = w_i = w_i/(w_1 + w_2), i = 1,2. \tag{9}$$

The output represents the weight of the decision rule.

Layers 4 - The output of the neurons are calculated by the product of the consequences of the rules. Parameters in this layer are referred to as "consequent parameters".

Layers 5 – The single node in this layer is a fixed model labeled Σ that compute the overall output as the summation of all incoming signals:

$$y = O_{5,i} = \sum_i \overline{w}_i f_i \tag{10}$$

This structure can be trained by any learning mechanism used in the Neural Networks [8].

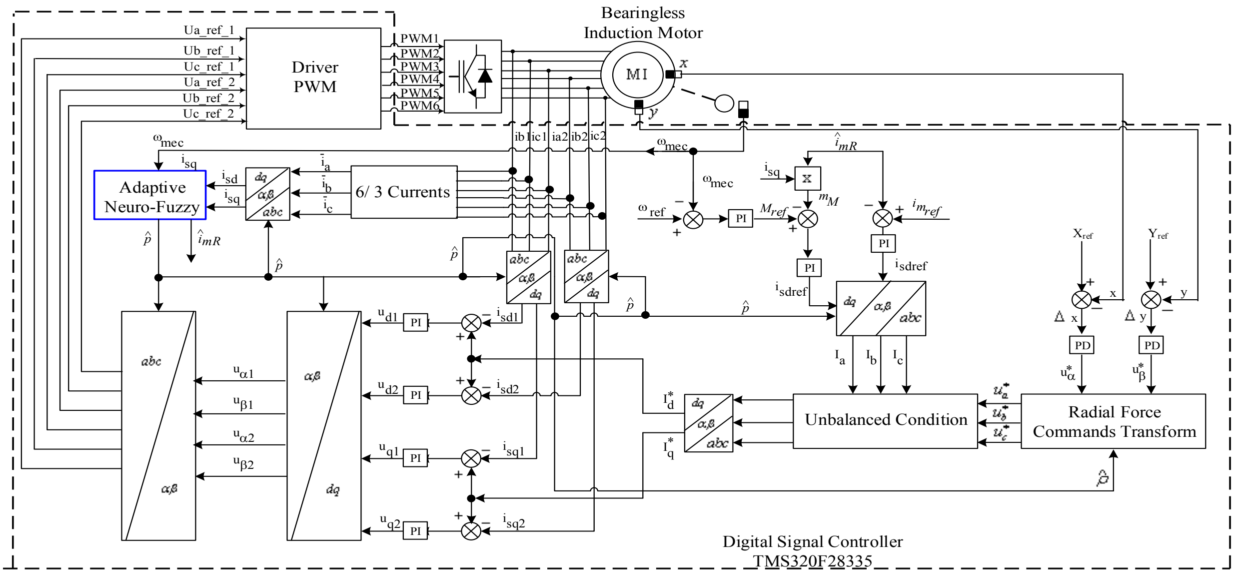
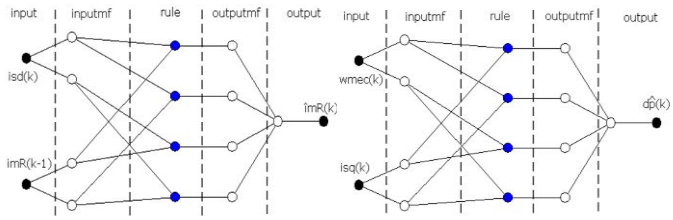


Figure 5. Block diagram of controller with implements DSP TMS 3208F28335.



(A) (B)

Figure 4. ANFIS 1 (A) -Estimation Magnetizing current and ANFIS 2 (B) - Estimation flux rotor.

The estimator of rotor flux used two ANFIS structures. The first structure estimates the magnetizing current and the second structure estimates was the rotor flux, Fig. 4.

It is possible observes in Fig. 4 that each node of the structure represents a layer ANFIS, Fig. 3. Although we do not have basic knowledge of the parameters adjustments, the initial parameter settings are designed by ANFIS. This system manages to achieve quick adjustments without the need knowledge the induction machine underlying dynamics.

The ANFIS training was performed from the conventional model presented in [6], using the nominal parameters of the induction machine without bearings with split winding which are given in Appendix A, in the condition of the rotor centered. The data of Tables I and II were obtained with ANFIS.

TABLE I. REGARDING TRAINING AND TESTING OF THE ANFIS 1.

MF Shape	*MF per entry*	*Rules*	*Epochs*	*Train.MSE*	*Test.MSE*
trimp	2	4	300	0.000105349	3.46523e-005
trapmf	2	4	300	9.97182e-005	2.79477e-005
gbellmf	3	9	500	7.71389e-005	1.26352e-005
gbellmf	**5**	**25**	**500**	**2.23735e-005**	**1.87042e-005**

TABLE II. REGARDING TRAINING AND TESTING OF THE ANFIS 2.

MF Shape	*MF per entry*	*Rules*	*Epochs*	*Train.MSE*	*Test.MSE*
trimp	2	4	300	0.0040629	0.00489893
trapmf	2	4	300	0.0039423	0.00482686
gbellmf	3	9	500	0.00170528	0.00241691
gbellmf	**5**	**25**	**500**	**0.00119589**	**0.00165979**

IV. SYSTEM DESCRIPTION COMPLETE

The stage of vector speed control was developed with the radial positioning controller and the current controllers. The Fig. 5 shows a block diagram of the proposed system. The radial positioning controller is compose by two PD controllers (Proportional-Derivative). These unbalanced currents try to compensate the position displacements. The current controllers are PI (Proportional-Integrative). The stage of control the rotor position was implemented in the paper [11]. One of the many contributions of this paper is continuity of the work [12] adding speed control based on Neuro-Fuzzy estimator.

V. SIMULATION RESULTS

The software environment used for this simulation was MATLAB® R2010a. The model of the induction machine adopted the balanced three-phase currents and despised the viscous friction of the bearings. These considerations were realized with the goal of approximation the motor conventional model with the model bearingless motor as in [6]. Fig. 6 shows the results of the ANFIS with different speeds.

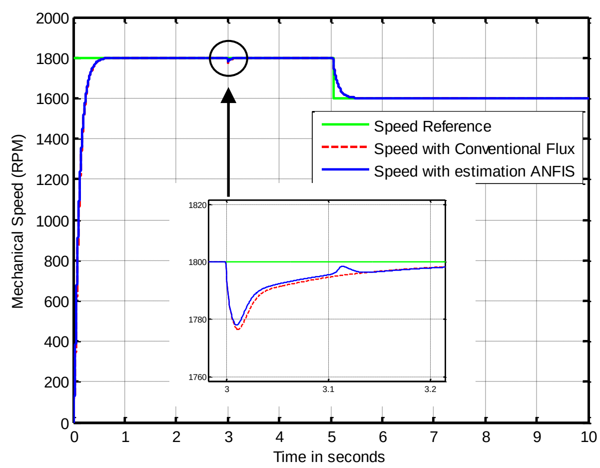


Figure 6. Behavior of speed with conventional flux and anfis.

The range of simulation time was 10 seconds. Fig. 6 show a better zoomed view for analysis of load variation: 0.028 N.m at the time of 3 seconds. Fig. 7 shows the performance of speed control by signal error obtained by conventional model,

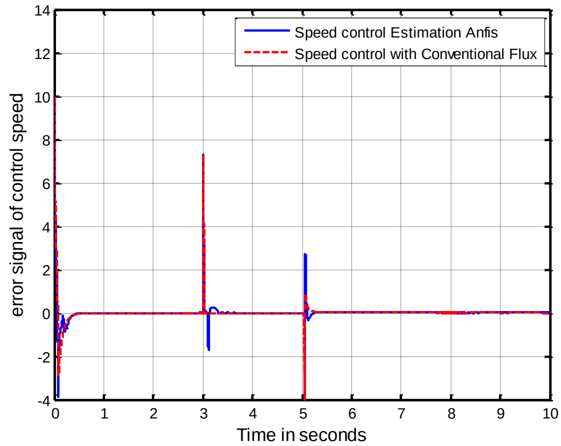


Figure 7. Behavior of error signal of speed control.

Fig. 7 referring to the amplitudes of the errors generated by the control time of 3 seconds while the load was applied in the instant process and 5 seconds in the speed change. Fig. 8

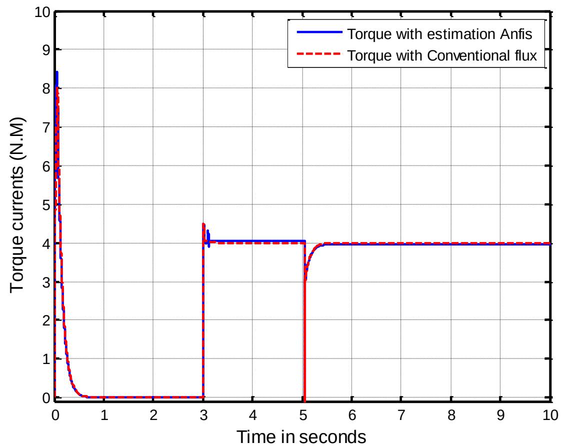


Figure 8. Behavior of torque currents.

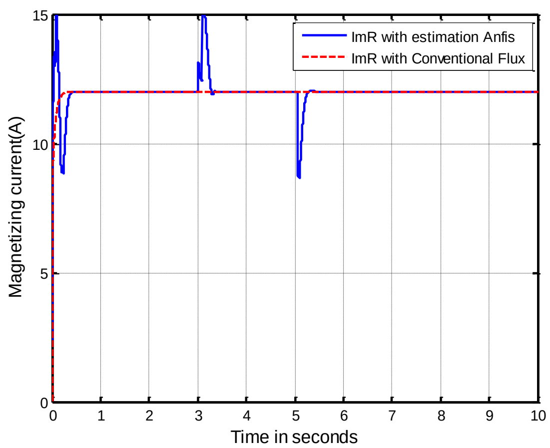


Figure 9. Behavior of magnetizing current.

Fig. 10 and 11 shows the current signal behavior $i_{Sd}(t)$ and $i_{Sq}(t)$. The signals currents tend to continuous and constant

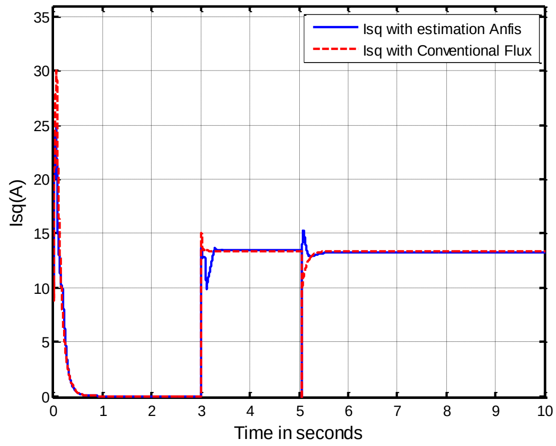


Figure 10. Behavior of quadrature component of stator current.

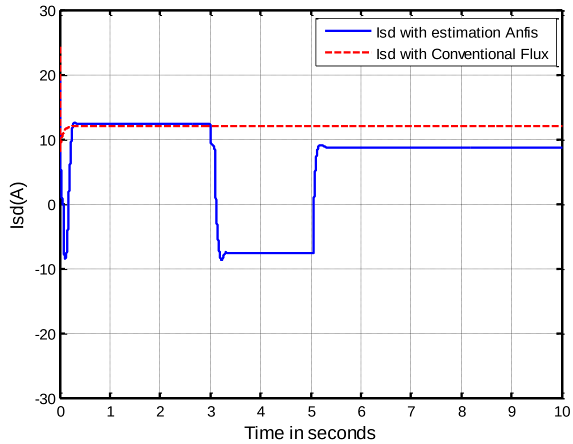


Figure 11. Behavior of direct component of stator current.

The Figure 12 shows the angular position in a zoom range from 0 to 0.4 seconds. Figure 13 shows rotor flux.

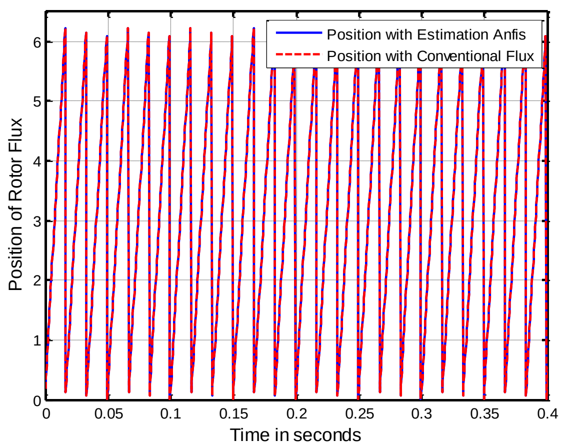


Figure 12. Behavior of position of rotor flux.

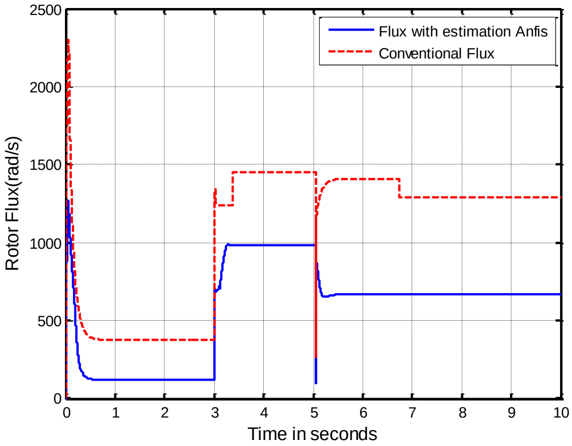


Figure 13. Behavior of rotor flux.

VI. CONCLUSION

This paper shows the implementation of an inference mechanism system – Neuro-Fuzzy what allows the representation of the knowledge structuralized in rules. It composes the Takagi-Sugeno model. Proposed systems have been simulated using MATLAB. This system used a set of data obtained by simulations.

The considered inference system proved itself capable of assisting or even replacing a human operator during real time process. The learning mechanism revealed itself efficient. The estimator ANFIS implemented was evaluated in close system loops. Results demonstrated the effectiveness of Neuro-Fuzzy estimator. Forthcoming researches will investigate estimator ANFIS in an experimental prototype in the laboratory worked in [12].

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APPENDIX A

R1	*Stator resistance*	*1,18 Ω*
R2	*Rotor resistance*	*1,42 Ω*
J	*Inertia moment*	*0,00995 kg.m2*
Ls	*Stator Inductance*	*6,56 mH*
Lr	*Rotor inductance*	*6,56 mH*
Lm	*Magnetizating inductance*	*0,14 H*

Ω = ohm, m =milli, H = Henry, mm = millimeter.