Adaptative Neuro-Fuzzy Inference System for Estimation of Rotor Flux of a Bearingless Induction Motor applied to Speed Control

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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) which is based in an input-output model is used to tune the membership functions in fuzzy system. ANFIS along with the backpropagation learning algorithm was applied to estimate the rotor flux and the magnetization current for the purpose of identifying bearingless induction motor angular speed. ANFIS 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 inference proposed system will be implemented in DSP's.

1 Introduction

There are urgent requirements for the controlling technology of bearingless motor in some scopes, such as sealed transmission of material, high-speed drive of machine tool spindle, aviation and aerospace realms etc. Thus, bearingless motor has become a new study hotspot (Bu Wenshao et. al, 2012). Flux estimation is an important part in induction machine control. The stator flux can be estimated from the measured terminal voltage and current. Once the stator flux is available, it is possible to calculate the rotor flux (Vitor, V. F. et. al; 2012). The flux information is needed in induction machine control for the purpose of synchronous angle and synchronous speed estimation, flux regulation and torque regulation.

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. Know that the fuzzy sets are used to represent vacant concepts, inexact (E. H. Mamdani. 1997). The Fuzzy Inference system (FIS) is a popular computing framework based on the concept of fuzzy set theory, fuzzy if-than rules, and fuzzy reasoning. Artificial Neural Network (ANN) learns from scratch by adjusting the interconnections between layers. A neuro-fuzzy system is simply a fuzzy inference system trained by a neural network learning algorithm. The adaptive Neuro-Fuzzy Inference System (ANFIS) combines fuzzy logic and artificial neural networks to evaluate estimation angle flux of a Machine Induction from direct currents and quadrature components stator current for the

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control of field coordinates. We used the MATLAB to represent the knowledge of the specialist (E. H. Mamdani, 1977) and to interpolate decisions containing uncertainties from the inputs. ANFIS is the fuzzy based paradigm that grasps the learning abilities of ANN to enhance the intelligent system's performance using a priori knowledge. Using a given input-output data set, ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned using either a backpropagation algorithm alone, or in combination with a least squares type of method (Patil, A.B.; Salunkhe, A.V., 2008).

ANFIS fully makes use of the excellent characteristics of the neural network and the fuzzy inference system, and is widely applied in many fields of fuzzy controller design and model identification. As a special neural network, ANFIS can approximate all nonlinear systems with less training data and quicker learning speed and higher precision. ANFIS is a neural network in fact, which realize sugeno fuzzy system using network. (Hou Zhi-xiang; Li He-qing., 2006). In Purwanto, E.; Arifin, S.; Bian-Sioe So. (2001) ANFIS was applied to estimate flux rotor and identity rotor angular speed of three-phase induction motor.

The vector control technique needs flow sensors to determine the exact value of the magnitude and of the position of the rotating flow. This limitation was resolved with the flux estimator based on vector machine model using as reference the rotor flux vector requiring only the stator phase currents and speed mechanics (Rodriguez, E.F.; Santisteban, J.A., 2011).

The results of our work showed a good result to estimation of flux with excellent stabilization variation of parameters of the motor. This study analyzes the performance of an adaptive neuro-fuzzy inference system for estimation of parameters of motor in order to counterbalance the limitations of the conventional observer.

The ANFIS simultaneously estimates flux speed and magnetization current that defines the rotor flux position (after integrating flux speed) and rotor flux magnitude. The arrangement of this paper is as follows. In Section II introduction the modeling of a bearingless induction motor with the parameters adopted of the induction motor. Section III explains the ANFIS structure. Section IV the results of simulated. Section V concludes this paper.

2 Modeling of a Bearingless Induction Motor

2.1 Parameters adopted of the Induction Motor

Fig. 1 shows an equivalent circuit of a conventional three phase, Induction Motor(IM) (per phase).

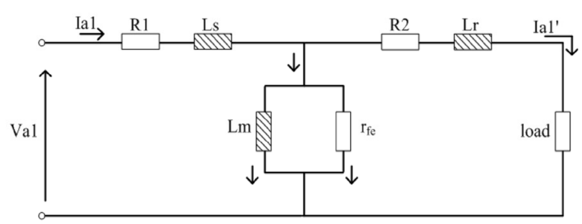


Fig. 1. Equivalent circuit of the machine used.

Where i_{a1} is stator current and i'_{a1} is the rotor current refer to stator**.** Others Motor parameters are listed in Table I.

TABLE I
EQUIVALENT CIRCUIT PARAMETERS OF THE MACHINE ELECTRICAL

Symbol	Parameter	Value[a]
R1	Stator resistance	1,18 Ω
R2	Rotor resistance	1,42 Ω
J	Inertia moment	0,00995 kg.m^2
Ls	Stator Inductance	6,56 mH
Lr	Rotor inductance	6,56 mH
L_m	Magnetizating inductance	0,14 H

[a]Ω = ohm, m =milli, H = Henry, mm = millimeter.

It includes some laboratory measured test parameters as (per phase) equivalent inductances or resistances (Vitor, V. F. et. al, 2012) to be used in simulation models.

2.2 Bearingless Machine with Divided Windings

The stator of the induction machine used has divided windings, as shown in Fig. 2. The rotor used in the machine performs better in controlling radial positioning and speed control (Victor, V.F. et. al, 2009). The currents applied to each half-winding are given by:

$$i_{a1} = i_a + \Delta i_{a1} \tag{1}$$

$$i_{a1}' = i_a - \Delta i_{a1} \tag{2}$$

$$i_{b1} = i_b + \Delta i_{b1} \tag{3}$$

$$i_{b1}' = i_b - \Delta i_{b1} \tag{4}$$

$$i_{c1} = i_c + \Delta i_{c1} \tag{5}$$

$$i_{c1}' = i_c + \Delta i_{c1} \tag{6}$$

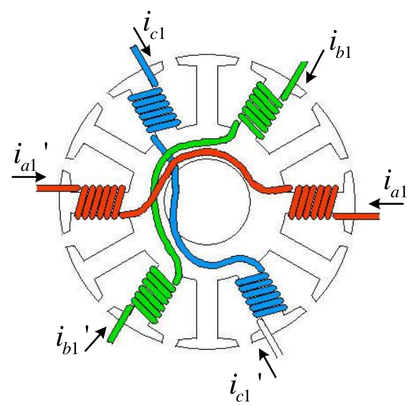


Fig. 2. Stator of an induction-type bearingless motor with divided windings.

2.3 Flux Model

The implemented system is based on the vector control technique that controls the induction machine (Leonhard, W., 2001). 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 (Ferreira, J. M. S., 2006) allowing the implementation of the speed and radial positioning controllers. The estimation of rotor variables was carried out using the rotor flux frame of reference, since it significantly simplifies the implementation of the digital system.

The state equations of the rotor flux are presented below according to the parameters of Table I, obtained by the expression for the electric torque, Eq. (7).

$$m_M = k.i_{mR} i_{Sq}, \quad k = \frac{2}{3}(1\text{-}\sigma).\mathrm{L_S} \tag{7}$$

Where m_M is the motor torque, i_{mR} is the magnetizing current representing rotor flux, i_{Sq} is the quadrature components of stator current, σ is the Scattering factor and $\mathrm{L_S}$ is the Stator inductance. Equation (8) describes magnetizing current and (9) difference load angle.

$$T_R \frac{di_{mR}}{dt} + i_{mR} = i_{Sd} \tag{8}$$

$$\frac{d\rho}{dt} = \omega_{mR} = \omega + \frac{i_{Sq}}{T_R i_{mR}} \tag{9}$$

Where i_{Sd} is the direct component of stator current, ω_{mR} is the angular velocities of the magnetising and stator current vectors. T_R is the Rotor time constant, R_R is the Rotor resistance, L_R is the Rotor inductance. The flux angle ρ, obtained by integration of (9). To solve this, recall that, calculate a lag time constant $T_R = L_R / R_R$.

$$J \frac{d\omega}{dt} = m_M - m_L \tag{10}$$

Where J is the inertia moment, m_L is the load torque. Equations (7-9), with the mechanical equation (10) constitute a model of the induction motor in field coordinates, as described by the block diagram in Fig. 3.

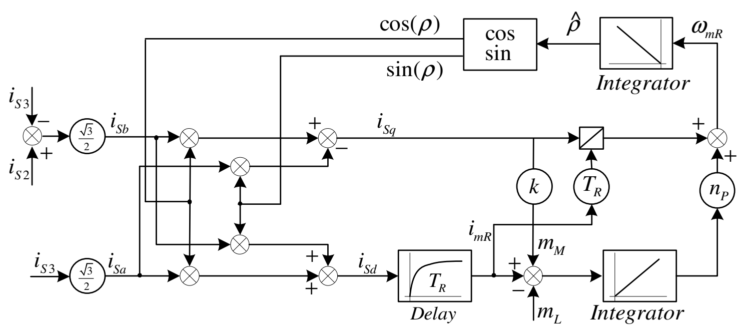


Fig. 3. Block diagram of induction motor in field coordinates, assuming impressed stator currents.

The idea of the principle of field coordinates control was suggested by Leonhard, W.(2001). Performance limitations arise mainly from inaccurate knowledge of these parameters or from the influence of external agents such as temperature or flux saturation. If parameter variation occurs, the estimation of rotor flux will display an error that will influence overall system performance (Victor, V.F. et. al; 2009).

2.4 System Description Complete

The Fig.4 shows a block diagram of the proposed system.

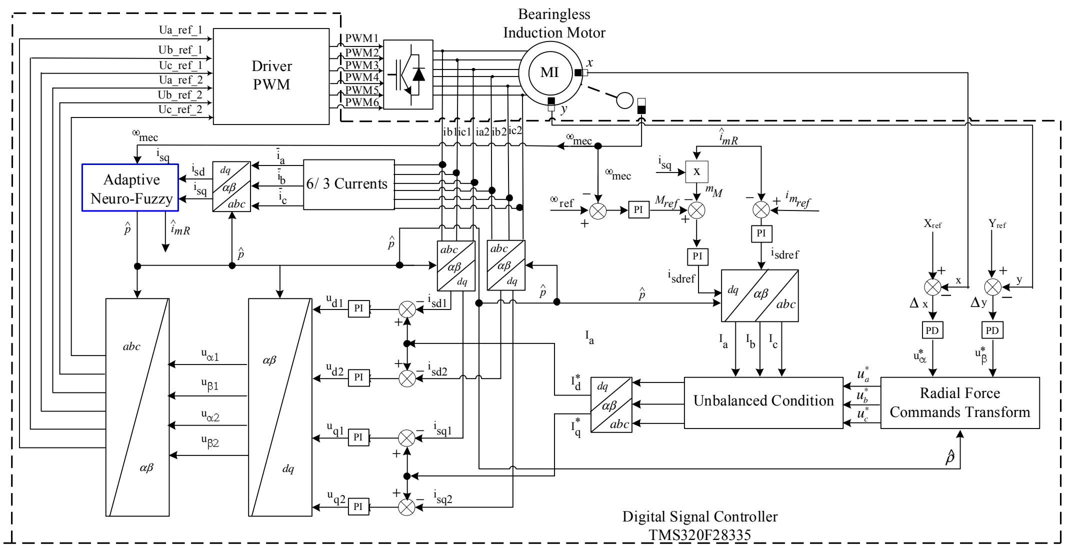


Fig. 4. Block diagram of controller with implements DSP TMS 3208F2812.

The stage of vector speed control is developed with the radial positioning controller and the current controllers – both will be implemented in DSP TMS320F28335. To implement the speed controller, a rotor flux referential is estimated. Thus, this model is reduced; therefore, the computational effort requested by DSP is minimized. The speed controller is composed by tree controllers PI (Proportional-Integrative), which apply the flux control and the rotational torque control. These two controllers must be operated decoupled.

The radial positioning controller is composed by two PD controllers (Proportional-Derivative). To accomplish the radial positioning control, the reference coordinates change from XY to abc coordinates, so that the control signals uα* and uβ* are transformed in ua , ub and uc signals. These control signals are added in one direction or subtracted from the reference currents Ia, Ib and Ic. These unbalanced currents try to compensate the position displacements. The current controllers are PI (Proportional-Integrative).

3 ANFIS STRUCTURE

The chosen Neuro-Fuzzy system was ANFIS (Adaptive Network-based Fuzzy Inference System) (Jang, J. S. R. 1993). 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 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 is based on the a Takagi-Sugeno first-class model (TS) (Takagi, T.; Sugeno, M.,1985). An example of this system can be seen as follows. It has two variable inputs – x and y; two variable outputs – f1 and f2; and the following rules (11) and (12):

$$IF\ x\ the\ A_1\ the\ y = B_1\ then\ f_1 = px + qx + r_1 \tag{11}$$

$$IF\ x\ the\ A_2\ the\ y = B_2\ then\ f_2 = px + qx + r_2 \tag{12}$$

The same system can be represented as an Adaptive Network-based Fuzzy Inference (ANFIS) as shown on Fig. 5.

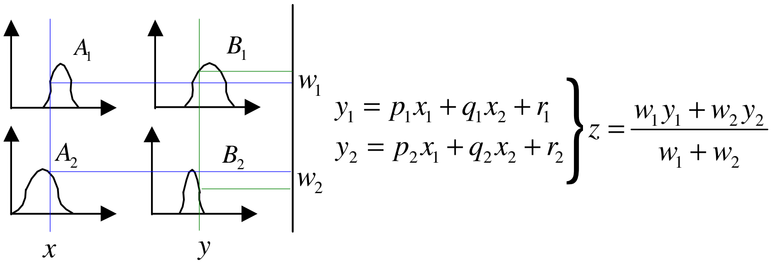


Fig. 5 – Firing of rules for different membership functions.

Where A the joint B is sets fuzzy. Follow the description of the layers of Fig. 6 (Takagi, T.; Sugeno, M., 1985).

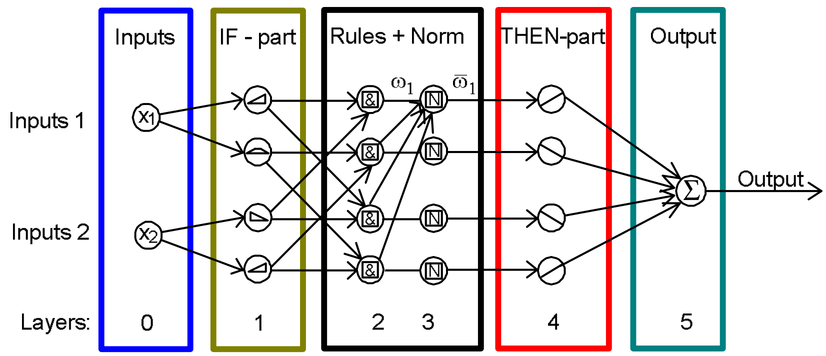


Fig. 6. ANFIS Structure.

Layers 1 - It calculates the relevancy degree with that the inputs satisfy the linguistic labels or terms associate to these we:

$$w_t = \mu_{Ai}(x)\mu_{Bi}(y), i = 1, 2. \tag{13}$$

Where w_t is a degree of membership for variable x to linguistical terms A_i, which are described by their membership functions. Membership functions $\mu_{A_i}(x)$ are usually defined as Bell functions:

$$\mu_{Ai}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}}, \tag{14}$$

Where $\{a_i, b_i, c_i\}$ denote parameters of adaptive nodes and are called premise parameters.

Layers 2 - Each knot of this layer corresponds to a rule and calculates with that degree the rule consequence this being then care of or either are the implications of the premises.

$$f(x, y) = \frac{w_1(x, y)f_1(x, y) + w_2(x, y)f_2(x, y)}{w_1(x, y) + w_2(x, y)} \Rightarrow \frac{w_1f_1 + w_2f_2}{w_1 + w_2} \tag{15}$$

Layers 3 - This layer carries through a normalization of the values of the previous layer.

$$\overline{w}_t = \frac{w_t}{w_1 + w_2} \quad (16)$$

The output represents the weight of the decision rule.

Layers 4 - In this layer the output of the neurons are calculated by the product of the consequences of the rules.

Layers 5 - We of this last layer they calculate the output of the ANFIS. Being able to be rewritten as:

$$f = \overline{w}_1 f_1 + \overline{w}_2 f_2 \quad (17)$$

This structure can be trained by any learning mechanism used in the Neural Networks Takagi, (T.; Sugeno, M., 1985 and Jang, J. S. R., 1993). This work carried out the training into two steps:

Step 1 – The parameters of the antecedents are fixed and the consequences are adjusted by the method of the squared minimums;

Step 2 – The parameters of the consequences are fixed and the antecedents are adjusted by the algorithm descending gradient;

The estimator of rotor flux used two ANFIS structures. The first structure estimates the magnetizing current and the second structure estimates the rotor flux, Figure 7.

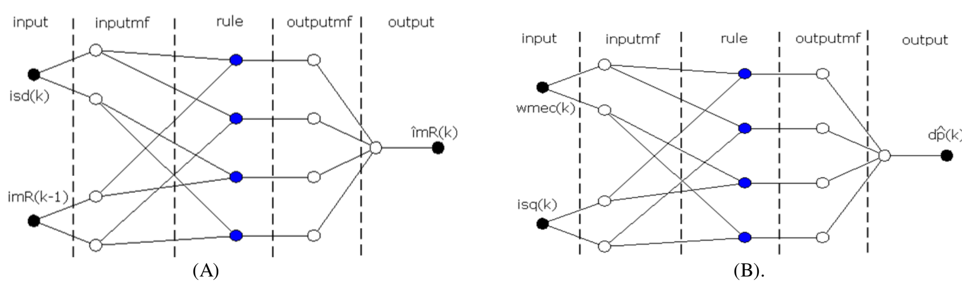


Fig. 7. ANFIS 1 (A) -Estimation Magnetizing current and ANFIS 2 (B) - Estimation flux rotor.

We can observe in Fig. 7 that each node of the structure represents an ANFIS layer, Fig. 6. 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 of the knowledge of the induction machine underlying dynamics.

The ANFIS system generated by the fuzzy toolbox available in MATLAB allows for the generation of the standard Sugeno style fuzzy inference system. The section 4 introduces the form of the design and analysis of the estimator ANFIS.

4 Design and Analysis

The simulation performance with the model of the induction machine considered the balanced three-phase power stage and despised the viscous friction of the bearings. These considerations were made with the goal of bringing the test model of the bearingless machine. We use MATLAB® R2010a, which already provided the ANFIS function.

The ANFIS training was performed from the conventional model presented in [7-10], using the nominal parameters of the induction machine without bearings with split winding shown in Table I, in the condition of the rotor centered. The parameters are selected using a hybrid optimization method, the membership function – *gbellmf*, the linear output membership function, error tolerance at zero and the number of epochs equals to 100.

Training input and output data were normalized using the command *mapminmax* of the MATLAB. The training process consisted of approaching the estimator ANFIS with the conventional estimator. The range of training time was 20 seconds, and the imposed variations are described below: Variation of the rotor time constant (every 2 seconds steps were applied in random variations of the order 0-50% on the nominal value of the constant). The criteria used are based on Paiva, José Álvaro. (2007).

The operation of ANFIS system at the MATLAB followed some steps; a set of membership function was chosen; load a set of input and output data to be used on the training of ANFIS; generate a FIS and validate the inference system. The section five shows the results of the estimation of rotor flux.

5 Results

This sections shows a detailed description of the simulated results from the modeling IM that was obtained in MATLAB. The complete estimation model was developed and simulated using ANFIS, which is a function available in MATLAB. An implementation tool was used for simulation. Euler was the discretization method used with the integration step 10^{-3}. The estimation ANFIS was utilized with two structures: two inputs and one exit, Fig. 7.

The final ANFIS 1 model has the following characteristics:

Number of nodes: 21
Number of linear parameters: 12
Number of nonlinear parameters: 12
Total number of parameters: 24
Number of training data pairs: 40201
Number of checking data pairs: 4021
Number of fuzzy rules: 4

We used 100 epochs for training and performance of estimation which was evaluated using root mean square error (RMSE). Minimal training RMSE = 9.32609e-009 and Minimal checking RMSE = 1.45662e-008 were obtained to first ANFIS structure. The results were very good for this application. In Fig. 8 shows the non-linear surface of the fuzzy model.

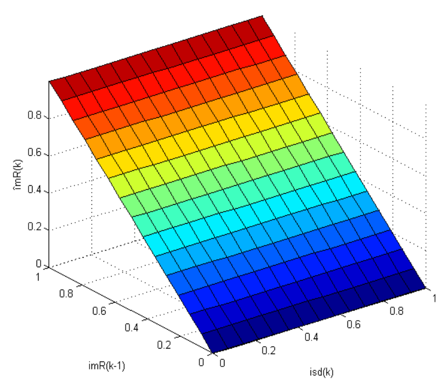


Fig. 8. Non-linear surface of the Sugeno fuzzy model with ANFIS 1.

After the adjustment of the premises and the consequences, Fig. 9 shows the respective obtained curves of training errors of ANFIS.

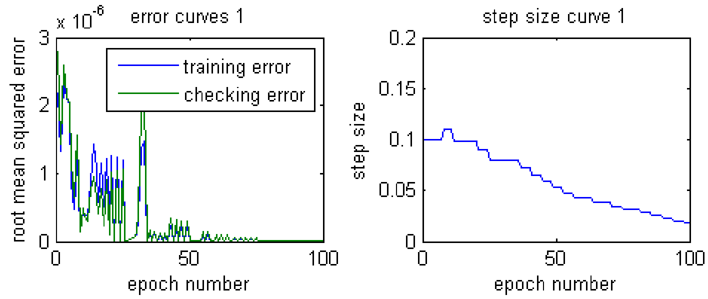


Fig. 9. Curve of Training of error to ANFIS 1.

The estimation of structure ANFIS 2 was also used with 100 epochs for training and obtained the Minimal training RMSE = 0.00172617 and Minimal checking RMSE = 0.00183409 to the second ANFIS structure. The final ANFIS 2 model has the following characteristics:

Number of nodes: 21
Number of linear parameters: 12
Number of nonlinear parameters: 12
Total number of parameters: 24
Number of training data pairs: 40201
Number of checking data pairs: 4021
Number of fuzzy rules: 4

In Fig. 10 show the non-linear surface of the fuzzy model.

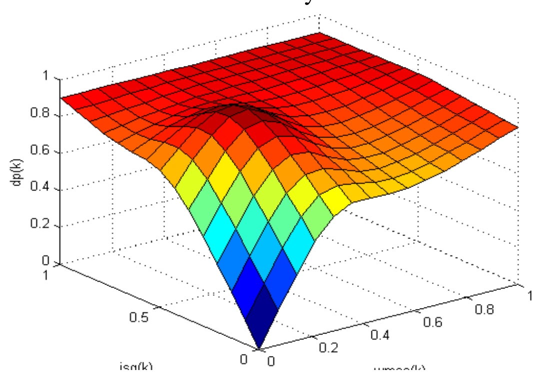


Fig. 10. Non-linear surface of the Sugeno fuzzy model with ANFIS 2.

After the adjustment of the premises and the consequences, Fig. 11 shows the respective obtained curves of error.

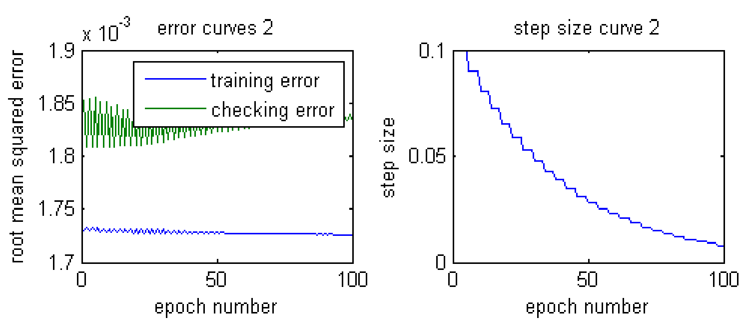


Fig. 11. Curve of Training of error to ANFIS 2.

Fig. 12 and Fig. 13 are menbership functions used in ANFIS system.

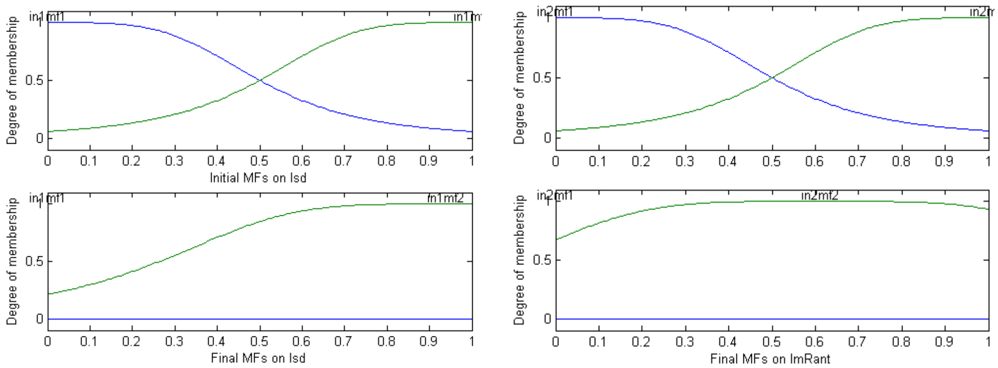


Fig. 12 – above: initial membership function chosen; below: final adjusted membership function

Note that in Fig. 12 some Membership functions were eliminated by the neural network training while in Figure 13 they were only adjusted.

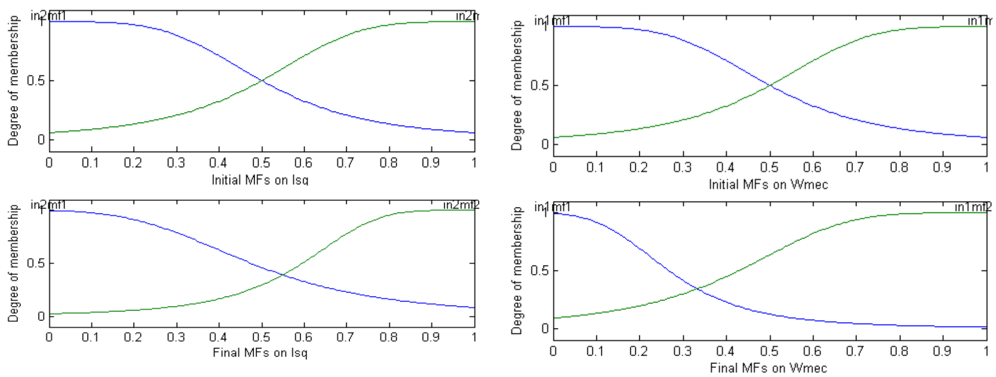


Fig. 13 - Menbership function were only adjusted.

The Fig. 14 shows the comparative analysis between conventional mechanical speed and the one estimated by ANFIS. Also, it shows the application of load variation: 0.04 N.m at the time of 10 seconds.

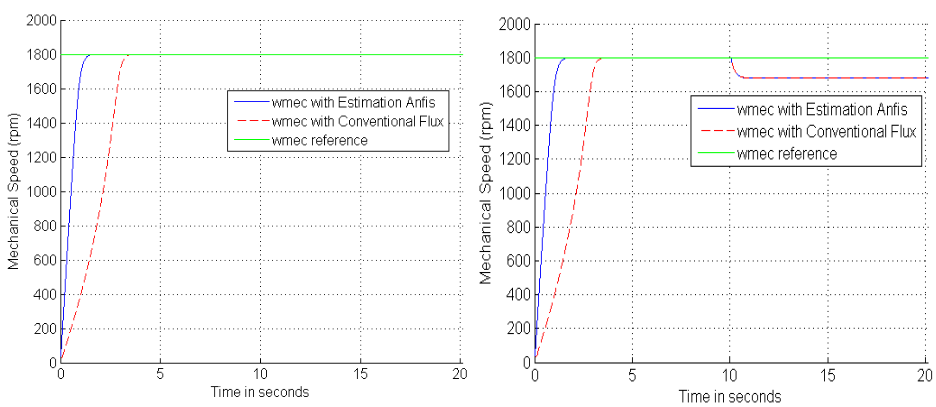
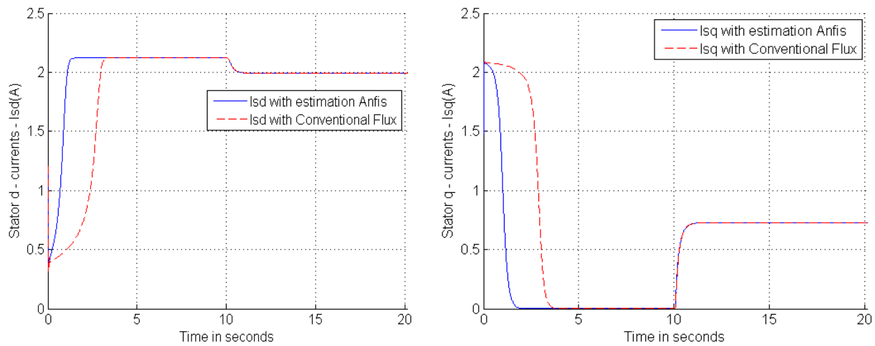


Fig. 14 shows comparative results between mechanical speed, obtained by conventional model, and estimation ANFIS.

Fig. 15 and 16 show current results after load application, obtained by conventional model, and estimation ANFIS.



(A) (B)

Fig. 15 shows comparative between currents: A shows stator d-currents and (B) shows stator q-currents with estimation ANFIS and conventional flux.

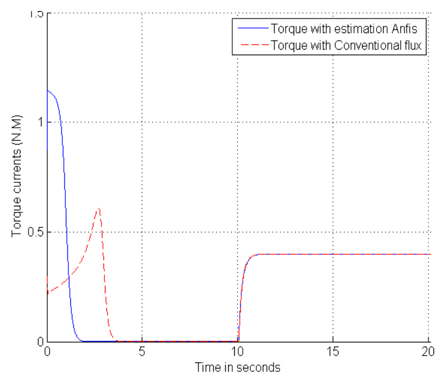
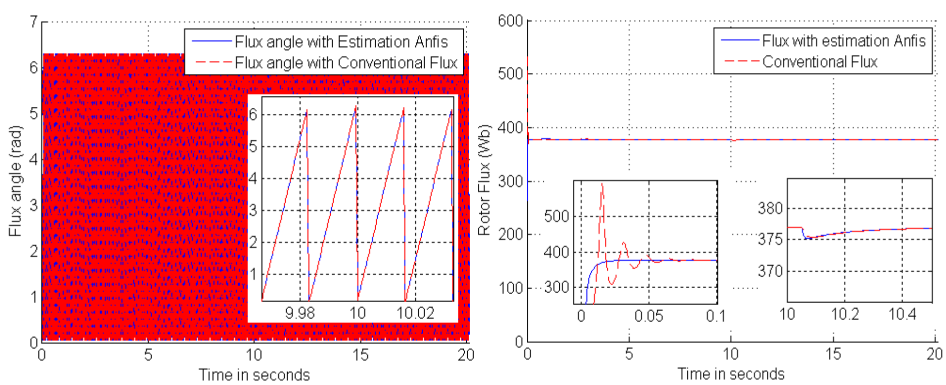


Fig. 16 shows comparative torque estimation results, obtained by conventional, model and estimation ANFIS.

Fig. 17 shows the rotor flux. We perceived a small variation of the rotor flux at the initial instants. Also, we verified a small variation of rotor flux on the application of the load in ten second application time. Fig. 17 B a better zoomed view for analysis.



(A) (B)

Fig. 17 shows comparative results between the conventional model and the ANFIS estimation model. Fig 17-A shows flux angle and Fig. 17-B shows rotor flux.

6 Conclusion

This paper shows the implementation of an inference mechanism system – Neuro-Fuzzy which 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. ANFIS estimators implemented were evaluated in open system loops in order to be eventually evaluated in closed system loops. Results demonstrated the effectiveness of Neuro-Fuzzy estimators. Forthcoming researches will investigate ANFIS estimator in a closed loop system with tree controllers: speed control, torque control and the magnetizing current control –all of which will be arranged in series.

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