NEURAL NETWORKS AND NEURO-FUZZY BASED STATES AND PARAMETERS ESTIMATION IN INDUCTION MOTOR SENSORLESS DRIVE

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Abstract – During the last decade, speed sensorless field-oriented control of induction motor has given a particular attention by researchers worldwide and a great number of papers have been published on this issue. In most of them, the authors proposed the speed estimation algorithms based on Kalman filter theory, neural networks and model of reference. In indirect vector control strategy, the accurate knowledge of the rotor resistance is critical to ensure field-orientation. However, very few papers have been published on the simultaneous estimation of the speed and the rotor resistance.
This paper describes the use of artificial neural networks and neuro-fuzzy networks for the simultaneous estimation of the speed, rotor flux and rotor resistance of an induction motor. This achievement is in authors' opinion a great contribution. Simulation results showed the effectiveness of the proposed schemes.

Keywords: Induction Motor, Field-Oriented Control, State Estimation, Artificial Neural Networks, Neuro-Fuzzy technique.

1 Introduction

Proposed by Blaschke in 1972 [1], Field-Oriented Control is a powerful control strategy that allows the achievements of high performance control with induction motor. The field-orientation is obtained by choosing an appropriate ***dq*** reference frame, with its ***d-axis*** aligned, and rotating synchronously with the rotor flux space vector. Under this condition, an induction motor behaves like a separately excited DC motor where the flux and the torque are controlled independently.

Field-oriented control for induction motors is now indisputably a standard control technique for electric machines. Adjustable speed drives (ASD) based on this technique are available on the market from leading drives manufacturers, and are the most widely used. However, these equipments require speed sensor providing the rotor speed feedback needed for the regulation purpose. This sensor increases the overall drive costs. In the last decade, significant efforts were made in the field of research on AC drive control to eliminate the need for the speed sensor. Speed sensorless field-oriented control of induction motor has given a particular attention by researchers worldwide and a great number of papers have been published on this issue [2]. In most of them, the authors proposed the speed estimation algorithms based on Kalman filter theory [3], model of reference [4] and neural networks [5].

In indirect vector control strategy, the accurate knowledge of the rotor resistance is critical to ensure field-orientation. As in the case of speed estimation for sensorless operation, many papers have been published emphasizing on the importance of the online tracking of the rotor resistance [6-7].

The simultaneous estimation of the speed and the rotor resistance is claimed by many researchers to be not feasible. The contrary was proven by a study published in 2002 [8], which is later confirmed by an other investigation [9].

This paper describes the use of artificial neural networks and neuro-fuzzy networks for the simultaneous estimation of the speed, rotor flux and the rotor resistance of an induction motor. This achievement is believed to be a great contribution. Simulation results showed the effectiveness of the proposed schemes. A comparison between these two artificial intelligence techniques regarding the learning time and the optimization error is also reported in this paper.

2 Induction Motor Modeling

The well-known induction motor mathematical model, in space vector notation, established in the stator-fixed reference frame is given by the following equations. Note that this reference frame is the most suitable for the observation of the internal machine variables.

$$\vec{V}_s = R_s \vec{I}_s + \frac{d\vec{\psi}_s}{dt} \tag{1}$$

$$0 = R_r \vec{I}_r + \frac{d\vec{\psi}_r}{dt} - j\omega_r \vec{\psi}_r \tag{2}$$

The stator flux space vector $\vec{\psi}_s$, the rotor flux space vector $\vec{\psi}_r$ and the electromagnetic torque are given by equations (3), (4) and (5) below, where $\vec{I}_s$ and $\vec{I}_r$ are respectively the stator current and the rotor current space vectors.

$$\vec{\psi}_s = L_s \vec{I}_s + L_m \vec{I}_r \tag{3}$$

$$\vec{\psi}_r = L_m \vec{I}_s + L_r \vec{I}_r \tag{4}$$

$$T_e = \frac{3pL_m}{2L_r}\left(\vec{\psi}_r \otimes \vec{I}_s\right) \tag{5}$$

Separating the machine variables into their real (α) and imaginary (β) parts will result in the fifth order induction motor model given by equation 6 below. The load torque is taken as unknown perturbation and the coupling between the electrical and the mechanical modes is considered, which is actually the case for small and medium power electrical machines.

$$\frac{d}{dt}\begin{bmatrix} I_{s\alpha} \\ I_{s\beta} \\ \psi_{r\alpha} \\ \psi_{r\beta} \\ \omega_r \end{bmatrix} = \begin{bmatrix} -\left(\frac{R_s}{\sigma L_s} + \frac{1-\sigma}{\sigma\tau_r}\right) I_{s\alpha} + \frac{L_m}{\sigma L_s L_r \tau_r}\psi_{r\alpha} + \frac{L_m \omega_r}{\sigma L_s L_r}\psi_{r\beta} + \frac{1}{\sigma L_s} V_{s\alpha} \\ -\left(\frac{R_s}{\sigma L_s} + \frac{1-\sigma}{\sigma\tau_r}\right) I_{s\beta} - \frac{L_m \omega_r}{\sigma L_s L_r}\psi_{r\alpha} + \frac{L_m}{\sigma L_s L_r \tau_r}\psi_{r\beta} + \frac{1}{\sigma L_s} V_{s\beta} \\ \frac{L_m}{\tau_r} I_{s\alpha} - \frac{1}{\tau_r}\psi_{r\alpha} - \omega_r \psi_{r\beta} \\ \frac{L_m}{\tau_r} I_{s\beta} + \omega_r \psi_{r\alpha} - \frac{1}{\tau_r}\psi_{r\beta} \\ \frac{3p^2 L_m}{2JL_r}\left(I_{s\beta}\psi_{r\alpha} - I_{s\alpha}\psi_{r\beta}\right) - \frac{F}{J}\omega_r - \frac{p}{J}T_l \end{bmatrix} \tag{6}$$

In (6), the coefficient of dispersion σ is given by:

$$\sigma = 1 - \frac{L^2{}_m}{L_s L_r} \tag{7}$$

In the case of rotor flux orientation, the rotor dynamics are given by the following equations.

$$\frac{d\psi_r}{dt} = \frac{L_m}{\tau_r} I_{sd} - \frac{1}{\tau_r}\psi_r \tag{8}$$

$$\frac{d\omega_r}{dt} = \frac{p^2 L_m}{JL_r}\left(I_{sq}\psi_r\right) - \frac{F}{J}\omega_r - \frac{p}{J}T_l \tag{9}$$

$$T_e = \frac{pL_m \psi_r}{L_r} I_{sq} \tag{10}$$

I_{sd} and I_{sq} are respectively the d and q components of the stator current space vector in the rotor flux coordinate system.

In sensorless operation, the rotor speed is jointly estimated with the rotor flux components and the rotor resistance. With the knowledge of the estimated rotor flux, the electromagnetic torque is obtained from (10)..

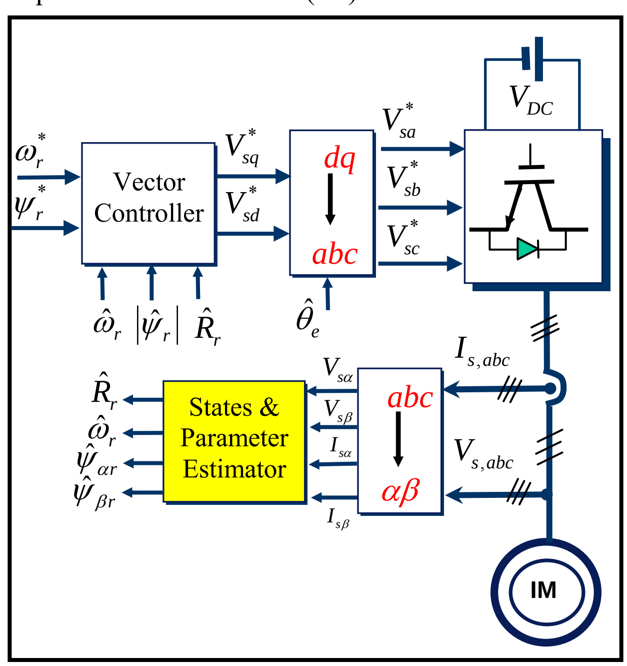

Fig. 1- Block diagram of IM Sensorless control

Figure 1 above gives a block diagram of an induction motor driven by a speed sensorless field-oriented controller. Speed, rotor flux components and rotor resistance are simultaneously estimated online

3 IM States & Parameters Estimation

States and parameters estimation is a part of signal processing field, and is used to obtain the non-measurable quantities of a given process. In the case of a cage induction motor, these non-measurable quantities are the rotor variables.

In this paper, two estimators are presented which are respectively based on artificial neural network and neuro-fuzzy network.

3.1 Artificial Neural Network (ANN) Estimator

It is well-known fact that artificial neural networks (ANN) can approximate a wide range of nonlinear functions with a high degree of accuracy. Their structures are built up with individual processing elements called neurons, which are highly interconnected to form layers. This high interconnectivity ensures very fast parallel computation to be obtained. Thanks to these advantages, ANN solutions have been recently suggested for online identification and sensorless control of electric drives.

In this paper, a three layer with one hidden layer perceptrons architecture is considered and the back-error-propagation algorithm (BEPA) was used for its training. The sigmoid functions are used at both the input and the hidden layers (Eq. 11), and the linear function is used at the output layer (Eq. 12).

$$f(x) = \frac{1}{1+e^{-x}} \tag{11}$$

$$f(x) = ax + b \tag{12}$$

Fig.2 below gives the structure of the ANN.

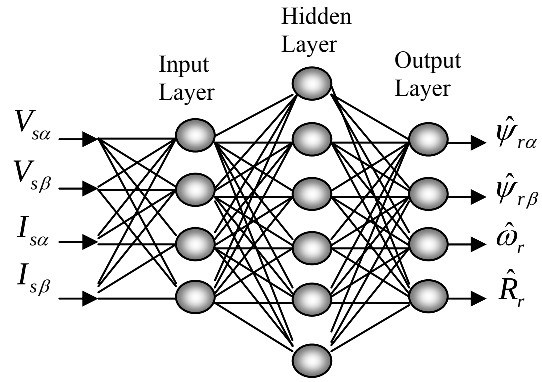

Fig.2 – Internal structure of the proposed ANN

The principle of the back-error-propagation algorithm is adapting the weights $\boldsymbol{w_{ij}}$ connecting the neuron $\boldsymbol{i}$ to $\boldsymbol{j}$, in order to minimize the energy function $\boldsymbol{E}$ of the error $\boldsymbol{\delta}$ between the actual and the desired outputs.

$$E = \frac{1}{2}\delta^T \delta \tag{13}$$

$$\Delta w_{ji} = -\mu \frac{\delta E}{\delta w_{ji}} \tag{14}$$

In (14), μ is the learning rate.

3.2 Neuro-Fuzzy Network (NFN) Estimator

Neuro-Fuzzy systems, also known as hybrid neural networks, combine the linguistic rule-based paradigms of fuzzy systems and the learning capability of artificial neural systems. The neural part of the system is used for signal processing, and the fuzzy part is used for reasoning task. This relatively new artificial intelligence technique has been given a great interest in the engineering community, and emerged as a powerful technique for real-time online identification and control of nonlinear dynamic systems.

In this paper, a Multi-Outputs Adaptive Neuro-Fuzzy Inference System (ANFIS) is adopted. As an example, fig 3 below gives the structure of a two-inputs, single output of ANFIS. In our case, the ANFIS has four inputs and four outputs.

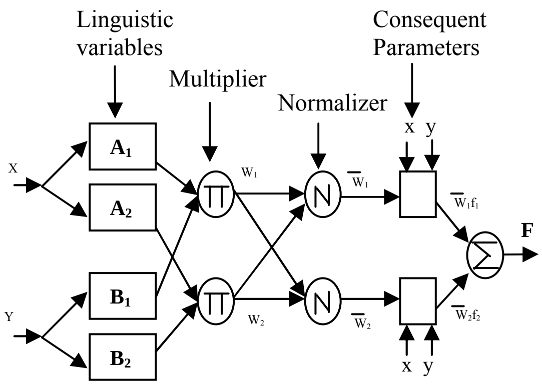

Fig.3 – Internal structure two-inputs, single output ANFIS.

3.3 Description of the NFN

Layer 1: In this layer, every node is adaptive characterized by a node function which is, example for the input x, given (15) below, where a_i, b_i and c_i are tuning parameters.

$$O_{1,i}=\mu_{Ai}(x)=\frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}},\quad i=1,2 \qquad (15)$$

Layer 2: Each node in this layer is constant and multiplies the incoming signals.

$$O_{2,i}=w_i=\mu_{Ai}(x)\,\mu_{Bi}(y) \qquad (16)$$

Layer 3: Each node in this layer is constant and defined by the function below.

$$O_{3,i}=\overline{w}_i=\frac{w_i}{\sum_{i=1}^{2}w_i} \qquad (17)$$

Layer 4: Each node in this layer is adaptive with a node adaptive function given below, where p_i, q_i and r_i are tuning parameters

$$O_{4,i}=\overline{w}_i f_i=\overline{w}_i\left(p_i x+q_i y+r_i\right) \qquad (18)$$

Layer 5: For this output layer, the output of the node is the summation of all the incoming signals.

$$O_{5,i}=\sum_{i=1}^{2}\overline{w}_i f_i=\frac{\sum_{i=1}^{2}w_i f_i}{\sum_{i=1}^{2}w_i} \qquad (19)$$

4 Simulation Block

The use of the oganigram shown in figure 4 below allows us to draw the state vector graphs [I_{ds}, I_{qs},Φ_{dr},Φ_{qr},ω_r], the rotor resistance, the electromagnetic torque and the corresponding errors [6][9][13][14]

Now, our main objective is to exploit Matlab/Simulink Software package in order to verify the effectiveness of the two proposed methods, Neural and Neural-Fuzzy Extended Kalman Filter (NEKF, NFEKF), for estimating simultaneously the induction machine parameters which are : flux, speed and rotor resistance.

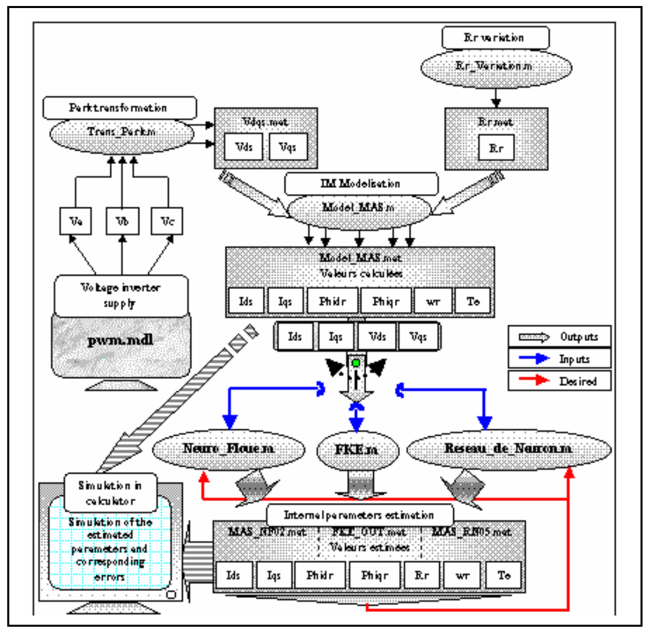

Fig.4 – Simulation global scheme

5 Simulation Programs

The EKF has allows us to achieve a best estimation of the induction motor internal parameters, so it is perfectly adapted to the time real estimation and additionally, it favorates a correct estimation at the transitory speed.

With respect to the ANNs, based on the back propagation method with gradient descent, we have also a main program which realise the network training. Notice that this program calling two data files, the first contain the NN inputs, which are the real values of the parameters, whereas the second present the desired output, which are the values estimated by the EKF.[13]

Finally, the Neuro-fuzzy program consists in loading two data files corresponding to inputs and outputs, in addition to running the training through an estimation loop which contain, in the first place, the loading of the input and output vectors, which are necessary in each loop cycle, after that, every vector is divided into two equal parts, the first serve like training data, whereas the second, serves us like a checking data [14]

6 Simulation Results

First, the induction motor model given in (6) is computed under Matlab software package. In this model, the rotor resistance R_r is supposed to be variable following the profile given in Fig. 4 below. It is clear that this scenario of R_r variation is the result of authors' imagination. These abrupt variations are used to test the convergence of the proposed estimators.

Simulation results are given below and show the effectiveness of ANN and FNN algorithms in simultaneous estimation of speed and internal variables of an induction motor.

Fig. 5 gives the actual and the estimated rotor resistance. Fig. 6 gives the actual and the estimated rotor angular speed. Fig. 7 gives the actual and the estimated rotor flux space vector magnitude. These results clearly demonstrate the superiority of Fuzzy-Neural Networks over traditional Artificial Neural Networks regarding the precision of approximation during transients.

7 Conclusion and Perspectives

We have presented the application of two emerged artificial intelligence techniques in the estimation of speed and internal variables and parameters on an induction motor for sensorless operation. Theses two techniques are artificial neural networks and neuro-fuzzy networks. Based on the fifth order model, simultaneous estimation of the rotational speed, rotor resistance and the rotor flux space vector is successfully achieved, and this achievement is believed to be a great contribution. As expected, simulation results showed the superiority of Fuzzy-Neural Networks over traditional Artificial Neural Networks regarding the precision of approximation during transients.

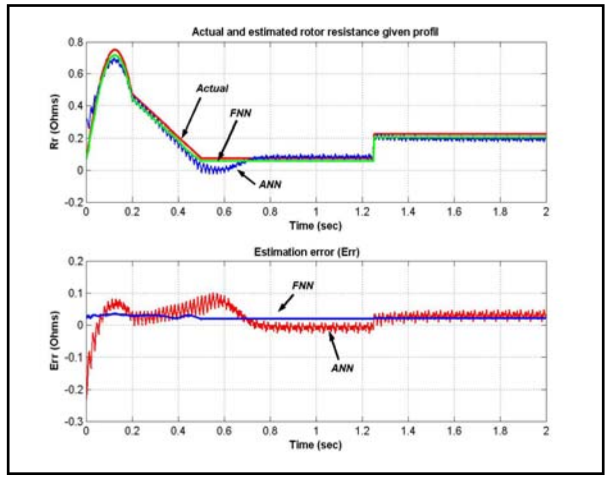

Fig.5 – Actual and estimated rotor resistance

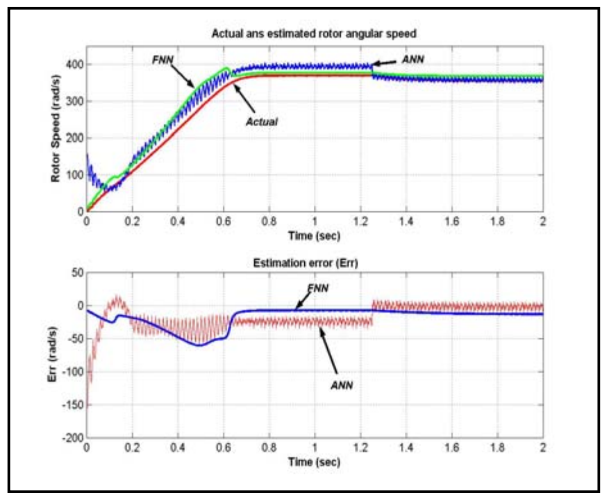

Fig.6 – Actual and estimated rotor speed

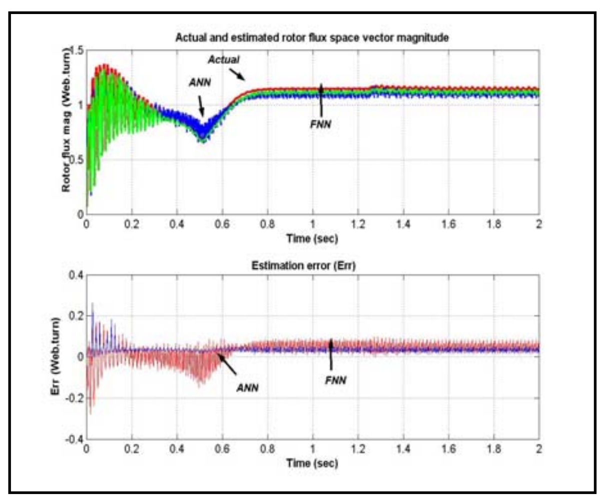

Fig.7 – Actual and estimated rotor flux magnitude

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