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Open-loop neuro-fuzzy speed estimator applied to vector and scalar induction motor drives

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ABSTRACT

Scalar and vector drives have been the cornerstones of control of industrial motors for decades. In both the elimination of mechanical speed sensor consists in a trend of modern drives. This work proposes the development of an adaptive neuro-fuzzy inference system (ANFIS) angular rotor speed estimator applied to vector and scalar drives. A multi-frequency training of ANFIS is proposed, initially for a *V*/*f* scheme and after that a vector drive with magnetizing flux oriented control is proposed. In the literature ANFIS has been commonly proposed as a speed controller in substitution of the classical PI controller of the speed control loop. This paper investigates the ANFIS as an open-loop speed estimator instead. The subtractive clustering technique was used as strategy for generating the membership functions for all the incoming signal inputs of ANFIS. This provided a better analysis of the training data set improving the comprehension of the estimator. Additionally the subtractive cluster technique allowed the training with experimental data corrupted by noise improving the estimator robustness. Simulations to evaluate the performance of the estimator considering the *V*/*f* and vector drive system were realized using the Matlab/Simulink® software. Finally experimental results are presented to validate the ANFIS open loop estimator.

1. Introduction

For many years several research institutes and industries have been working in strategies of driving the induction motor (IM) in a high performance context. These researches have been focusing on new control strategies, modeling of the machine, estimation techniques as new materials and assembly methods as well.

Vector controlled drives provide high performance of the IM as the separately excited DC machine. Several vector control techniques have been proposed in the literature for many years. The most stressed of them is the Field Oriented Control (FOC). In FOC vector control [1], the torque of the machine is controlled indirectly. The main characteristic of this kind of control is the desired decoupling of the flux and torque components of the space phasor of stator currents.

The FOC control can be implemented in two different schemes: direct and indirect. In the indirect FOC (IFOC) the flux vector is determined through the slip speed and the knowledge of the angular rotor position. The rotor speed can be measured directly from the motor shaft using an encoder, a tachometer or a resolver. This measure increases the total cost of the drive system, reduces the security and in several cases are infeasible. To eliminate the mechanical sensor in vector controlled drives observers and estimators of the rotor speed have been constantly proposed in the literature. Actually this subject is a trend in induction motor drives [2]. Drives without mechanical sensors are named sensorless drives [3,4]. Classical techniques to estimate the rotor speed include the model reference adaptive systems (MRAS) [5], Luenberger state observers [6], Extended Kalman Filter (EKF) observer [7,8], high-frequency injection [9], saliency effects, among others.

The emerging techniques of speed estimation include soft computing for determining the mechanical speed. Artificial Neural Networks (ANN) [10] and Neuro-fuzzy systems can be applied in such task. Historically the ANN has been most widespread than other soft computing technique in the power electronics and motor drives applications [11,12]. In [13] an ANN was used as speed estimator in a vector drive. Recently some works have been considered the application of ANN combined to model reference adaptive systems (MRAS) in sensorless drives. In [14] the voltage model of the MRAS was substituted by an ANN model becoming the model free of pure integration and less sensitive to stator resistance variations. In

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Nomenclature

ω_{mm}	angular speed of the magnetizing flux oriented reference frame
ω_{sl}	angular slip speed
$\oplus$	direct sum
F	overall function implemented by the adaptive network
H	arbitrary function
i_{mm}	instantaneous value of magnetizing current
i_{sx}	instantaneous value of direct component stator current
i_{sy}	instantaneous value of quadrature component stator current
L_m	magnetizing inductance
L_s	stator inductance
$O(k)$	predicted network output for the pattern k
$p = d/dt$	differential operator
r_a	positive constant
r_b	positive constant
R_s	stator resistance
S	set of parameters
$T(k)$	desired network output for the pattern k
T_{r1}	rotor leakage time constant
T_r	rotor time constant
u_{sx}	instantaneous value of direct component stator voltage
u_{sy}	instantaneous value of quadrature component stator voltage
$\mathbf{i}$	vector of input variables
J	moment of inertia
n	number of training pattern
P	number of pole-pairs

[15] a neural MRAS has been proposed using TLS EXIN neuron concept and in [16] a neural based reduced order observer is proposed. In [5] the MRAS scheme was implemented in a vector controlled drive.

The adaptive neuro-fuzzy inference systems (ANFIS) [17] is presented in this work as a good alternative for estimating the machine parameters such as the angular rotor speed [18,19]. However, in the literature, ANFIS have been extensively used for control not for estimation. In [20,21] the PI controller of the speed control loop was substituted by a self-tuned neuro-fuzzy controller. The same characteristic application is found in [22]. In [23] an adaptive sliding mode neuro-fuzzy control was proposed as a speed controller. Several applications, on the other hand, consider the ANFIS and ANN in the fault diagnosis of motors [24–29]. Some works consider the soft computing to estimate the machine parameters like rotor and stator resistance in vector controlled drives [26,30]. In [31] ANFIS is used to track the maximum power point in a wind generation system.

Open-loop estimators has always been attracted attention in determining the speed in induction motor drives because of its simplicity and low-cost profile [32].

In [33] a fuzzy system was combined with an open-loop motor model based estimator to improve the performance of the last one. A moderate performance drive was achieved in that work. Nevertheless the tests were carried out in a narrow speed range operation.

This paper contributes with this subject proposing an open-loop neuro-fuzzy speed estimator with an innovative development. The ANFIS package of the Matlab/Simulink® software was used to train and check the estimator response using the hybrid learning training algorithm and the subtractive clustering to generate the fuzzy inference system.

At first, a speed estimator for a *V*/*f* is proposed. To know the rotor speed in this kind of drive is important when the speed regulator is based upon the slip calculation. Unlike other works the root mean square (RMS) values of direct and quadrature voltages and current signals are used for training the ANFIS and good results were obtained for non sinusoidal voltages in the stator. To determine the ANFIS structure directly from training data set the subtractive clustering method [34] was used. As the drive will be submitted to several reference speeds the whole spectrum of associated command frequencies was dived in equal parts. This technique has been resulted in an efficient training method and used to the vector drive as well.

After that a ANFIS based speed open-loop estimator is proposed to an indirect magnetizing flux oriented drive. The most used FOC for induction motors is the rotor FOC scheme due to its inherent decoupling between the flux and torque components of the stator space phasor currents. The evaluation of the ANFIS estimator in the magnetizing flux reference frame is one more contribution of this work. Moreover, despite of the ANN training which is sensitive to noise, the ANFIS estimator was trained in the experimental setup with experimental data and presented a good response under this situation.

This paper is divided as follows: Section 2 presents the magnetizing flux oriented control; Section 3 presents the ANFIS basis; Section 4 presents the hybrid learning algorithm used to train the ANFIS; Section 5 presents the subtractive clustering used to generate the membership functions to the ANFIS incoming signals; development of the neuro-fuzzy speed estimator to the *V*/*f* drive is presented in Section 6; Section 7 presents the same development to the IFOC drive. Finally, the estimation errors, the impact of the rotor resistance changes, the experimental results and the conclusions are presented.

2. Magnetizing flux oriented control

To control the induction motor a magnetizing flux oriented control with impressed stator currents is proposed [3]. The most usual field oriented technique is the rotor field orientation. In this work magnetizing flux oriented control was used because of its coupling of direct and quadrature stator current components. This coupling implies in a nonlinearity of the drive and for this reason the open loop estimator proposed in this work is operating in more severe conditions. Following the basis of this control is presented.

2.1. Magnetizing flux orientation equations

From generic reference frame the stator and rotor equations in the magnetizing reference frame were derived according to Fig. 1. Eqs. (1) and (2) present the direct and quadrature components of stator voltages in the magnetizing reference frame and Eqs. (3) and (4) present the quadrature and direct components of stator currents in the magnetizing reference frame derived from rotor equations:

$$u_{sx} = R_s i_{sx} + (L_s - L_m) p i_{sx} + L_m p i_{mm} + \omega_{mm}(L_m - L_s) i_{sy} \tag{1}$$

$$u_{sy} = R_s i_{sy} + (L_s - L_m) p i_{sy} + L_m \omega_{mm} i_{mm} + \omega_{mm}(L_s - L_m) i_{sx} \tag{2}$$

$$\frac{i_{mm} + T_r p i_{mm}}{T_{r1}} = p i_{sx} + \frac{i_{sx}}{T_{r1}} - \omega_{sl} i_{sy} \tag{3}$$

$$\omega_{sl}\left(i_{mm}\frac{T_r}{T_{r1}} - i_{sx}\right) = p i_{sy} + \frac{i_{sy}}{T_{r1}} \tag{4}$$

where u_{sx} is the instantaneous value of direct component stator voltage, u_{sy} is the instantaneous value of quadrature component stator voltage, i_{sx} is the instantaneous value of direct component