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Neural speed estimator for line-connected induction motor embedded in a digital processor

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A B S T R A C T

Estimating the electrical and mechanical parameters involved in three-phase induction motors is frequently employed to avoid measuring every variable in the process. Among mechanical parameters, speed is an important variable: it is involved in control, diagnosis, condition monitoring, and can be measured or estimated by sensorless methods. These technologies offer advantages when compared with direct measurement, such as lower cost or more robust systems. This paper proposes the use of artificial neural networks to estimate rotor speed by using current sensors for balanced and unbalanced voltage sources with a wide mechanical load range in a line-connected induction motor. This paper also presents two case analyses: (i) a single current sensor; and (ii) a multiple currents sensors. Simulation and experimental results are presented to validate the proposed approach. A neural speed estimator embedded in a digital processor is also presented.

1. Introduction

Three-phase induction motors (TIMs) are used in many industrial applications such as pumps, fans, machine tools and robotics as a key element in the conversion of electrical into mechanical energy. Several control strategies for these machines are based on electronic drives with sensorless technologies, which is a growing trend in TIM monitoring and control [1].

Conventional methods based on direct measurement of machine variables, such as torque and speed, have some disadvantages, in addition to the higher cost involved with the driver implementation. Rotor speed can be measured with optical encoders, electromagnetic resolvers or brushless DC tachogenerators. However, the use of these electromechanical devices is subject to limitations, such as increased driver costs, reduced mechanical robustness, and low noise immunity. They also affect machine inertia and require special attention in hostile environments [2].

The use of sensorless techniques is primarily found in induction motor control drives [3–5]. However, induction motor speed is also an important variable to be considered in condition monitoring [6–8] and fault detection [9–11]. The main approaches for speed estimation are open-loop estimators using monitored stator voltage and current, state observers, model reference adaptive systems, and artificial intelligence [2].

The conventional numerical methods for speed estimation are based on machine models. In this case, speed can be calculated by using machine model equations which require voltage and current as local machine parameters. Other variables for equation solving are the electrical and mechanical parameters of the machine, e.g., resistances, inductances, and load inertia, which are unavailable in the machine nameplate to feed the equations [12].

The disadvantages of this method are: (i) unavailable parameters, such as resistances and inductances in the machine nameplate to feed the equations; (ii) the need to solve machine equations; (iii) most models are linear; and (iv) substantial computing power is required in the application.

Condition monitoring is one of the applications of the speed estimators. The work of D'Angelo et al. [11] proposed approach is related to the enhanced resilience of the new motor failure detection procedure against false alarms, combined with a good sensitivity that allows the detection of rather small fault signals. The proposed system monitors the instantaneous values of the motor currents i_{as}, i_{bs}, i_{cs} and the rotor speed ω [11]. Furthermore, control drives plays also an important role of intelligent speed estimation. For example, the work of paper [5] proposed an open-loop neuro-fuzzy speed estimator with an innovative development. The

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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 [5].

More recently, the work presented in [13] proposed a method based on a complex continuous wavelet transform using a complex shifted Morlet wavelet to estimate the instantaneous rotation speed of electrical machinery. Also, as an alternative method, reference [14] used an approach to evaluate instantaneous speed of electrical machines by using the information from the time–frequency distribution of a vibration signal.

Artificial neural networks (ANNs) have been presented as an alternative strategy to state observers for estimating the speed of rotating machinery. The work in [15] presents a speed estimator based on an adaptive linear element (ADALINE) network. The inputs of the proposed structure are the voltages and currents in the *abc* axis. A neural speed estimator of a TIM using a multilayer perceptron (MLP) is presented in [16]. The inputs in this estimator are data from the current and stator voltages in three-phase synchronous axis coordinate **dq0**. More recently, the authors of [3] proposed an alternative methodology, based on artificial neural networks, for estimating the speed of a TIM driven by a voltage source inverter with space vector modulation under the scalar control strategy.

Line connected induction motors can use simple drive systems such as delta-wye connection. However, it is expected that the speed reaches between 90% and 95% of its rated speed for switching from wye to delta position in TIM. In Ref. [17] the authors mentioned that, depending on the application, the drive can go from a star connection to delta with 50% of rated speed. Thus there is a need to measure – or estimate – the TIM speed in order to determine the exact instant (or approximate) key switch.

The main objective of this paper is to introduce an efficient neural approach for estimating speed in line-connected induction motors by using the current root mean square value under balanced and unbalanced voltage sources, with different mechanical load conditions. The computational simplicity and robustness to the variation of power parameters and load change in the shaft are very important issues in estimating speed. The currents are the ANN inputs, while the rotor speed is the estimated output. The use of the primary variables of the induction motor as input signals is one of the differential aspects of this speed estimation approach. The currents are relatively simple to measure, requiring a current transducer and its signal conditioning. In this work two cases are analyzed: (i) with a single current sensor; and (ii) with three current sensors. The best performance neural network is embedded in a digital processor.

The proposed method, which considers unbalanced voltages and different kinds of loads applied to the induction motor, is based on offline training of the ANN. The currents are quite simple to measure from the data acquisition driver, and the processing cost of the monitoring system is reduced to simple matrix solving after the neural network is trained.

ANNs have been used to solve engineering problems [1,3,6,9,16,18,19] and have the following advantages: (i) after training, an ANN is reduced to a weight matrix processing and some sigmoid function operations; (ii) matrix solving requires less computing effort compared to equation solving for a conventional speed estimator; (iii) machine parameters are represented by the network weights; and (iv) the portability of the solution means less expensive hardware.

Recently, several neural network-based methods applied to induction motor-related problems have also provided effective results. An ANN is a processor with broad parallel-distribution and a natural propensity for storing experimental knowledge and making it available for use. The main advantage of an ANN used in this study is its ability to approximate nonlinear functional relationships.

This paper is organized into five sections. The modeling aspects of the TIM are presented Section 2. Section 3 explains the methodology used in TIM speed estimation. Sections 3.1 and 3.2 discuss simulation and experimental results, while the conclusions appear in Section 4.

2. Mathematical modeling of the induction motor

The first step involved in the design of an ANN is to compile a set of input–output patterns to adjust its internal parameters. This procedure is also known as the training process, wherein the network must be exposed to sequences of patterns which represent the desired behavior of the analyzed system.

For the purpose of generating the training patterns for the speed estimation system, various simulations are carried out using Matlab/Simulink software. The induction motor model used in the simulations is developed by [20], and is accepted and used by many researchers as a model which closely resembles real motor variables [20,21]. This model takes into account various aspects involved in motor electromechanical dynamics, which enable its behavior from transient to steady-state to be simulated in several operating configurations. The mathematical modeling of this complex machine is initially based on the stator voltage and rotor voltage equations. The equations related to the stator voltages are given by:

$$V_{as} = i_{as} r_s + \frac{d\lambda_{as}}{dt} \tag{1}$$

$$V_{bs} = i_{bs} r_s + \frac{d\lambda_{bs}}{dt} \tag{2}$$

$$V_{cs} = i_{cs} r_s + \frac{d\lambda_{cs}}{dt} \tag{3}$$

where V_{as}, V_{bs}, V_{cs} are three-phase voltages of the stator in Volt (V); i_{as}, i_{bs}, i_{cs} are three-phase currents of the stator in Ampere (A); λ_{as}, λ_{bs}, λ_{cs} are three-phase fluxes of the stator in Weber (Wb); and r_s is the stator resistance. In relation to the rotor, the voltage equations are provided by:

$$V_{ar} = i_{ar} r_r + \frac{d\lambda_{ar}}{dt} \tag{4}$$

$$V_{br} = i_{br} r_r + \frac{d\lambda_{br}}{dt} \tag{5}$$

$$V_{cr} = i_{cr} r_r + \frac{d\lambda_{cr}}{dt} \tag{6}$$

where V_{ar}, V_{br}, V_{cr} are three-phase voltages of the rotor in Volt (V); i_{ar}, i_{br}, i_{cr} are three-phase currents of the rotor in Ampere (A); λ_{ar}, λ_{br}, λ_{cr} are three-phase fluxes of the rotor in Weber (Wb); and r_r is the rotor resistance. The joint flux equations between the rotor and stator windings appear in the following matrix:

$$\begin{bmatrix} \lambda_s^{abc} \\ \lambda_r^{abc} \end{bmatrix} = \begin{bmatrix} L_{ss}^{abc} & L_{sr}^{abc} \\ L_{rs}^{abc} & L_{rr}^{abc} \end{bmatrix} \cdot \begin{bmatrix} i_s^{abc} \\ i_r^{abc} \end{bmatrix} \tag{7}$$

where

$$\lambda_s^{abc} = [\lambda_{as} \lambda_{bs} \lambda_{cs}]^T \tag{8}$$

$$\lambda_r^{abc} = [\lambda_{ar} \lambda_{br} \lambda_{cr}]^T \tag{9}$$

$$i_s^{abc} = [i_{as} i_{bs} i_{cs}]^T \tag{10}$$

$$i_r^{abc} = [i_{ar} i_{br} i_{cr}]^T \tag{11}$$