NEURAL NETWORK FOR IDENTIFICATION OF INDUCTION MACHINE PARAMETERS

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Abstract: This article presents a method for identification of induction machine parameters using artificial neural networks. The induction machine is a nonlinear multivariable dynamic system with parameters that vary with temperature, frequency, saturation and operating point. Considering that neural networks are capable of handling time varying nonlinearities due to their own nonlinear nature, they are suitable for application in induction machine systems.

Key words: artificial neural network, induction machine, indirect control, stator resistance

1. INTRODUCTION

Induction motor control systems are known to be extremely nonlinear control systems, because of induction motor parameter variability under different conditions. Heating of motor windings depends on stator and rotor currents leading to variability of stator and rotor resistances. Variable mutual inductance is a consequence of different flux levels of the motor. This is very important from the viewpoint of field oriented control systems. Most types of field oriented control systems are sensitive to errors resulting from non-constant parameters and furthermore, do not give an accurate representation of the machine under consideration.

In the past, many methods have been developed for estimations of induction machines parameters. Some of these methods are based on artificial neural networks (ANN) that replace the adaptive model of an induction machine. The basic structure of an adaptive scheme for stator or rotor resistance identification is shown in fig.1. This scheme is based on the model reference adaptive system (MRAS) [1].

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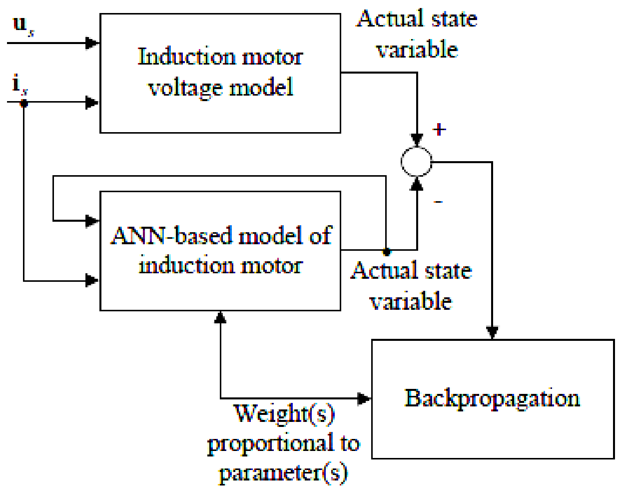

Fig. 1. ANN-based parameter identification.

2. ANN-BASED INDIRECT CONTROL SYSTEM.

The MRAS theory is utilized in order to estimate the rotor speed of induction motor. The rotor flux space-vector is estimated in the reference frame by the voltage model (reference model) and by the ANN-based model (adaptive model) of the induction motor.

In classical induction machine control systems, knowledge of the controlled system in the form of a set of algebraic and differential equations is required. This set of equations, written in a synchronously rotating reference frame is as follows [2]:

$$O = \frac{1}{T_r}\Psi_r - \frac{L_m}{T_r} i_s + s\Psi_r + j\left(\omega_e - \omega_r\right)\Psi_r \tag{1}$$

where T_r is the rotor time constant and s is the Laplace operator ($=d/dt$) and u_s is:

$$u_s = \left(R_s + \left(s + j\omega_e\right)\sigma L_s\right) i_s + \left(s + j\omega_e\right)\frac{L_m}{L_r}\Psi_r \tag{2}$$

The following example shows a method of the stator resistance identification in the IRFO control system (fig.2) [3]. Conventionally, the current model is used as the adaptive model because it is the rotor speed-dependent one. The difference between flux space-vectors estimated using the two ways is then used in an adaptive mechanism that outputs the estimated value of the rotor speed and adjusts the adaptive model until good performances are obtained. The inputs to the reference model are the direct- and quadrature-axis stator voltages and currents of the induction motor and the angular stator frequency ω_e. The outputs of the reference model are the components of the rotor flux space-vector in the d, q reference frame, which can be obtained from equation (2) as follows [4]:

$$\frac{d\Psi_{rd}}{dt} = \frac{L_r}{L_m}\left(u_{sd} - \hat{R}_s i_{sd} - \sigma L_s \frac{di_{sd}}{dt} + \omega_e \sigma L_s i_{sq}\right) + \omega_e \Psi_{rq} \tag{3}$$

$$\frac{d\Psi_{rq}}{dt} = \frac{L_r}{L_m}\left(u_{sq} - \hat{R}_s i_{sq} - \sigma L_s \frac{di_{sq}}{dt} - \omega_e \sigma L_s i_{sd}\right) - \omega_e \Psi_{rd} \tag{4}$$

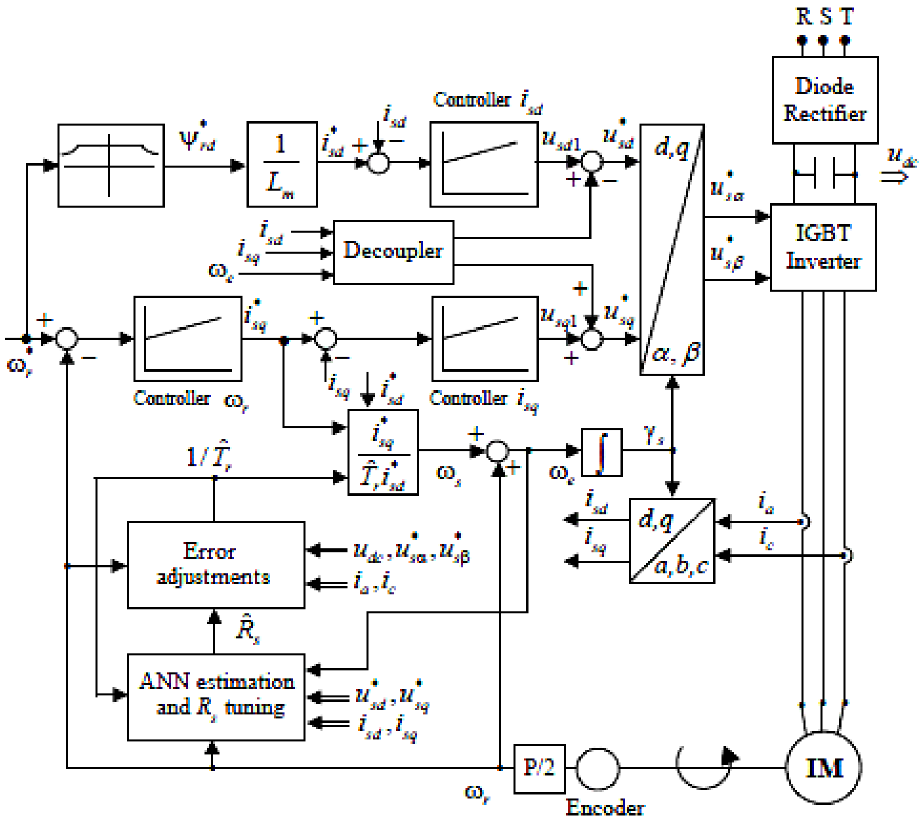

Fig. 2. ANN-based indirect rotor field-oriented control system.

3. ANN-BASED STATOR RESISTANCE

Equations (3) and (4) determine the reference model as shown in fig. 3. These equations do not contain the rotor speed. However, equation (1) contains the rotor flux space-vector and the rotor speed as well. This is the equation for the adaptive model. Rewriting (1) to give the rotor flux components in the d,q reference frame yields:

$$\frac{d\hat{\Psi}_{rd}}{dt} = \frac{1}{\hat{T}_r}\left(L_m i_{sd} - \hat{\Psi}_{rd}\right) + \left(\omega_e - \omega_r\right)\hat{\Psi}_{rq} \tag{5}$$

$$\frac{d\hat{\Psi}_{rq}}{dt} = \frac{1}{\hat{T}_r}\left(L_m i_{sd} - \hat{\Psi}_{rq}\right) - \left(\omega_e - \omega_r\right)\hat{\Psi}_{rd} \tag{6}$$

Equations (5) and (6) contain the rotor speed, which is generally changing, and the intent is to estimate this speed by using an ANN.

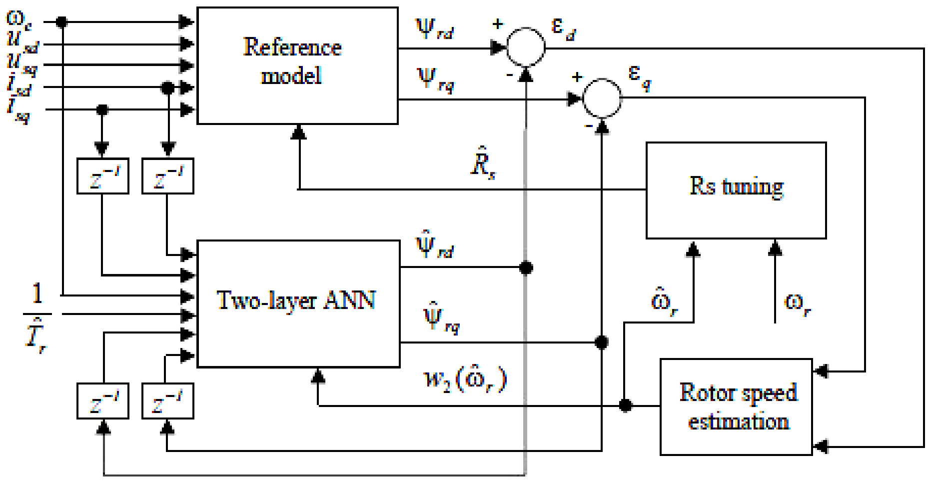

Fig. 3. Stator resistance tuning based on ANN

When there is no mismatch between the actual and identified parameters of the induction motor, then the errors ε_d and ε_q (fig. 3) are zero in the steady state. In this case, the rotor speed estimated by the ANN must be the same as the actual rotor speed. During transient states, there is a difference between the actual rotor speed and the speed estimated by the ANN, even if there is no mismatch between the actual and identified parameters of the induction motor. In these cases, the errors ε_d and ε_q are not zero, and they are used to adjust the weights of the ANN.

Otherwise, when there is any mismatch between the actual and identified parameters of the induction motor, then the errors ε_d and ε_q are not zero in the steady state. Consequently, the actual rotor speed is different from the estimated rotor speed. Taking into account the constant magnetizing level of the induction motor (constant mutual inductance), the difference between the actual and the estimated rotor speed can be caused by the following two reasons:

a) incorrect rotor resistance identification (incorrect inverse rotor time constant);
b) incorrect stator resistance identification.

4. ANN FOR ROTOR FLUX ESTIMATION

The stator resistance is an important parameter for inverse rotor time constant identification, especially in the low speed region. When the stator resistance is incorrectly identified, then the inverse rotor time constant is incorrectly identified as well. As a result, there is a mismatch between the actual rotor speed and the estimated rotor speed in the steady state.

When the stator resistance is correctly identified, then there is no mismatch between the actual rotor speed and the estimated rotor speed, and the inverse rotor time constant is correctly identified. As a result, the stator resistance tuning can be done either by a manual tuning procedure observing the difference between the actual rotor speed and the estimated rotor speed or by an automated fuzzy logic principle as will be described.

There are many methods for estimation of the rotor time constant. One group of online rotor time constant adaptation methods is based on the principles of MRAS. This is the approach with relatively simple implementation requirements. Replacing the actual rotor flux space-vector Ψ_r with the estimated rotor flux space-vector Ψ_r, in equation (1), and rewriting equations (1) and (2) in the α, β reference frame (ω_e=0), yields:

$$O = \frac{1}{\hat{T}_r}\hat{\Psi}_r - \frac{L_m}{\hat{T}_r} i_s + s\hat{\Psi}_r - j\omega_r \Psi_r \tag{7}$$

$$u_s = \left(\hat{R}_s + s\sigma L_s\right) i_s + s\frac{L_m}{L_r}\Psi_r + K_1\left(\Psi_r - \hat{\Psi}_r\right) \tag{8}$$

where K_1 is an observer gain.

A hat above a symbol in (7) and (8) denotes identified parameters. Equation (7) gives an estimation of the rotor flux space-vector based upon easily measured stator currents and rotor speed. This estimation mainly depends on the accuracy of the inverse rotor time constant identification.

Equation (7) presents an *adaptive model* of the rotor flux estimation [5]. On the other hand, (8) gives an estimation of the rotor flux space-vector based upon measured stator currents and the reconstructed voltage space-vector from the measured DC link voltage and the inverter driving signals.

Equation (8) is independent of the inverse rotor time constant and, accordingly, can be used as the reference model of the rotor flux space-vector estimation. This estimation mainly depends on the accuracy of the stator resistance identification.

The error signal of the rotor flux magnitude of the two estimators is applied to drive an adaptive mechanism (PI) which provides correction of the inverse rotor time constant.

5. CONCLUSION

Induction motors have a unique and important role in industry and electricity generation. Their main advantage is the elimination of all sliding contacts, resulting in a very simple and rugged construction. Induction machines are built in a variety of designs with ratings from a few watts to tens of megawatts.

Because of their nonlinear nature, induction motors are somewhat difficultly controlled. Considering that artificial neural networks are capable of handling time varying nonlinearities due to their own nonlinear nature, they are suitable for application in induction machine systems.

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