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Artificial Neural Network based Sensorless Vector Control of Induction Motor Drive

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Abstract. Controlled induction motor drives without mechanical speed sensors at the motor shaft have the attractions of low cost and high reliability. For these speed sensorless AC drive system, it is key to realize speed estimation accurately. This paper describes a Model Reference Adaptive System (MRAS) based scheme using Artificial Neural Network (ANN) for online speed estimation of sensorless vector controlled induction motor drive. The neural network has been then designed and trained online by employing a back propagation network (BPN) algorithm. The estimator was designed and simulated in Matlab. Simulation result shows a good performance of speed estimator. Also Performance analysis of speed estimator with the change in resistances of stator is presented. Simulation results show this estimator robust to resistances of stator variations.

Introduction

Induction motors are electromechanical systems suitable for a large spectrum of industrial applications, due to its high reliability, relatively low cost, and modest maintenance requirements [1]. Control of the Induction motors can be done using various techniques. Most common techniques are: (a) constant voltage/frequency control (V/F), (b) field orientation control (FOC) and (c) direct torque control (DTC).

Since the late 1980s, speed-sensorless control methods of induction motors using the estimated speed instead of the measured speed have been reported. They have estimated speed from the instantaneous values of stator voltages and currents using induction motor model. Other approaches to estimate speed use Extended Kalman Filter (EKF), Extended Luenberger Observer (ELO) and Model Reference Adaptive System (MRAS) [2]. Induction motor is highly coupled, non-linear dynamic plant, and its parameters vary with time and operating conditions. Therefore, it is very difficult to obtain good performance for the entire speed range using previous methods.

Recently, the use of Artificial Neural Network (ANN) to identify and control nonlinear dynamic systems has been proposed because they can approximate a wide range of nonlinear functions to any desired degree of accuracy [3]. It is a major advantage of ANN based techniques that they do not require any mathematical model of the motor under consideration and the drive development time can be substantially reduced [4]. In the paper, the speed estimator, based on ANN based Model Reference Adaptive System (MRAS) has been studied and analyzed. In ANN the back propagation network (BPN) algorithm is used for online training of neural network to estimate the motor speed.

Dynamic Model of Induction Motor

The dynamic model of the IM is derived by transforming the three phase quantities into two phase direct and quadrature axes quantities. The mathematical model in compact form can be given in the stationary reference frame as follows [5]. Where the voltage equation is:

$$V_{qs} = R_s i_{qs} + \frac{d\psi_{qs}}{dt} + \omega_e \psi_{ds} \tag{1}$$

$$V_{ds} = R_s i_{ds} + \frac{d\psi_{ds}}{dt} + \omega_e \psi_{qs} \tag{2}$$

$$V_{qr} = R_r i_{qr} + \frac{d\psi_{qr}}{dt} + (\omega_e - \omega_r)\psi_{dr} \tag{3}$$

$$V_{dr} = R_r i_{dr} + \frac{d\psi_{dr}}{dt} + (\omega_e - \omega_r)\psi_{qr} \tag{4}$$

where, V_{qr}, V_{dr}= 0 and P, denote the pole number of the motor. If the vector control is fulfilled, the q component of the rotor field ψ_{qr}would be zero. Then the electromagnetic torque is controlled only by q-axis stator current and becomes:

$$T_e = \frac{3PL_m}{4L_r}(\psi_{dr} i_{qs}) \tag{5}$$

Speed Estimation Using Neural Network

In MRAS technique, some state variables, X_d, X_q (e.g. rotor flux-linkage components, ψ_{dr}, ψ_{dr}, or back emf components, e_d, e_q, etc.) of the induction machine (which are obtained by using measured quantities, e.g. stator voltages and currents) are estimated in a reference model and are then compared with state variables $\hat{X}_d$, $\hat{X}_q$ estimated by using an adaptive model. The difference between these state variables is then formulated into a speed tuning signal (ε), which is then an input into an adaptation mechanism, which outputs the estimated rotor speed ($\hat{\omega}$).
Speed estimator using ANN is a part of a MRAS, where ANN takes the role of the adaptive model. ANN contains the adjustable and constant weights and the adjustable weights are proportional to the rotor speed. The adjustable weights are changed by using the error between the outputs of the reference and adaptive model. Fig. 1 shows the MRAS-based speed estimation scheme, which contains an ANN with BPN adaptation technique [6].

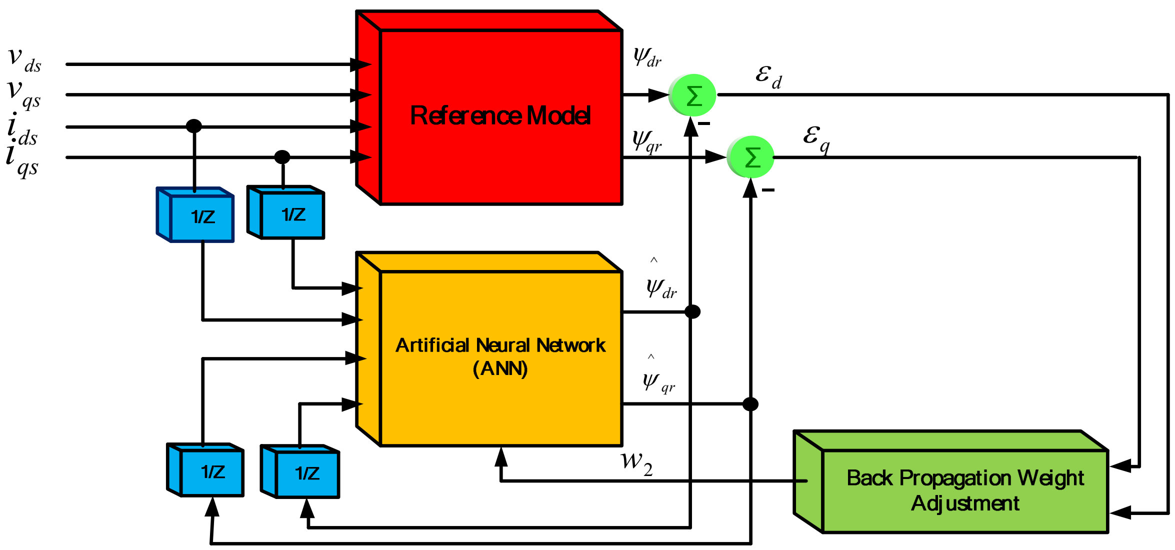

Fig.1.MRAS-based rotor speed estimator containing an ANN

The equations of adaptive model are given by

$$\widehat{\psi}_{dr} = \frac{1}{T}\int L_m\, i_{ds} - \widehat{\psi}_{dr} - \omega_r T_r \widehat{\psi}_{qr})dt \tag{6}$$

$$\widehat{\psi}_{qr} = \frac{1}{T}\int L_m\, i_{qs} - \widehat{\psi}_{qr} - \omega_r T_r \widehat{\psi}_{dr})dt \tag{7}$$

It is possible to implement equations (6) and (7) by a two layer ANN containing weights,

W_1 (= 1-c), W_2 (= $\omega_r T_r c$), W_3 (=$c l_m$). Where C=$\frac{T}{T_r}$, T, T_r are sampling time and rotor time constant. The variable ANN weight w_2 is proportional to the rotor speed. By using the backward difference method, the equation of adaptive model is given below.

$$\widehat{\psi}_{dr}(k) = w_1\widehat{\psi}_{dr}(k-1) - w_2\widehat{\psi}_{qr}(k-1) + w_3 i_{ds}(k-1) \tag{8}$$

$$\widehat{\psi}_{qr}(k) = w_1\widehat{\psi}_{qr}(k-1) - w_2\widehat{\psi}_{dr}(k-1) + w_3 i_{qs}(k-1) \tag{9}$$

That gives the value of rotor flux at K^{th} sampling instant. These equations can be visualized by the very simple two layers ANN shown in Fig. 2.

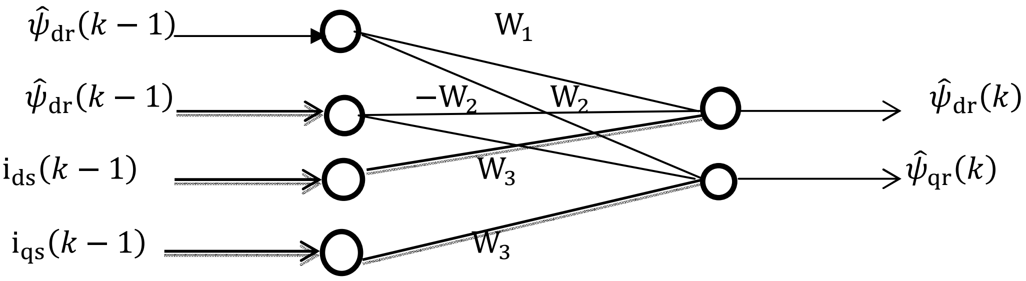

Fig.2. ANN model for the estimation of rotor flux linkage

After taking learning factor η and momentum term α into account, the estimated rotor speed is given below.

$$\widehat{\omega}_r(k) = \widehat{\omega}_r(k-1) + \frac{\eta}{T}\begin{Bmatrix} -[\psi_{dr}(k) - \widehat{\psi}_{dr}(k)]\widehat{\psi}_{qr}(k-1) \\ +[\psi_{qr}(k) - \widehat{\psi}_{qr}(k)]\widehat{\psi}_{dr}(k-1) \end{Bmatrix} + \frac{\alpha}{T}\Delta w_2(k-1) \tag{10}$$

Simulation and Results

For the simulation, a three- phase, four-pole induction motor was selected and, accompanied by the suggested ANN based speed estimator, were implemented in Matlab/Simulink. The response of ANN based speed estimator is compared with actual machine, as shown in Fig. 3.

Here, the stator resistance is changed from its actual value to 1.5 times the actual value in the form of step. The load torque, as shown in Fig. 4, went to positive and negative values in a step manner. Reference speed is changed from 0 to 300 rpm as shown in Fig. 4. It is clear that the estimated speed is again matching with the reference speed. Thus, the robustness of proposed drive to the variation of the stator resistance is confirmed. The parameters for the motor: Rated power, Rated voltage and Rated current are 2hp, 220V and 2.1A. Stator resistance and Rotor resistance are 10 and 6 ohm. Stator inductance and Rotor inductance are 0.5 H.

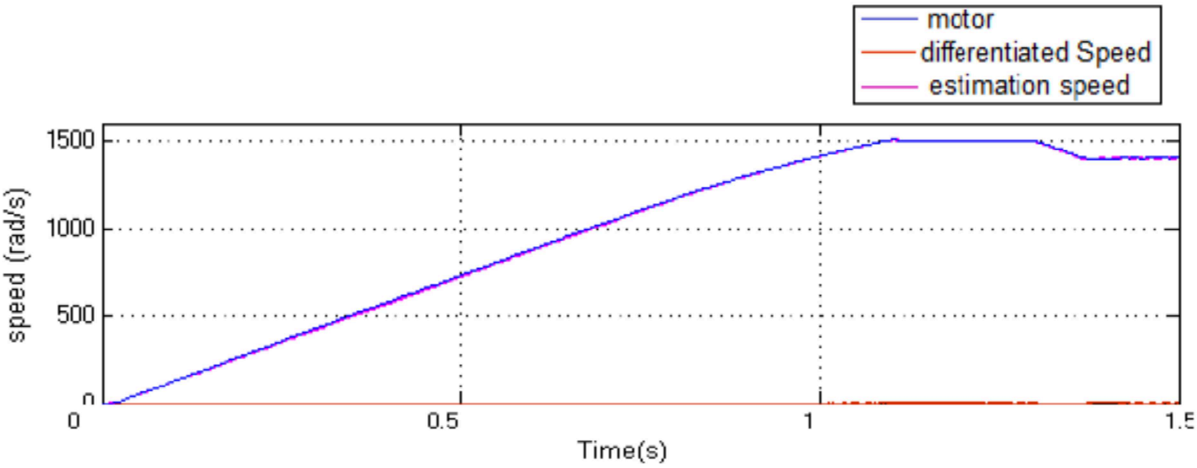

Fig.3.Response comparison of actual machine and ANN based speed estimator with error

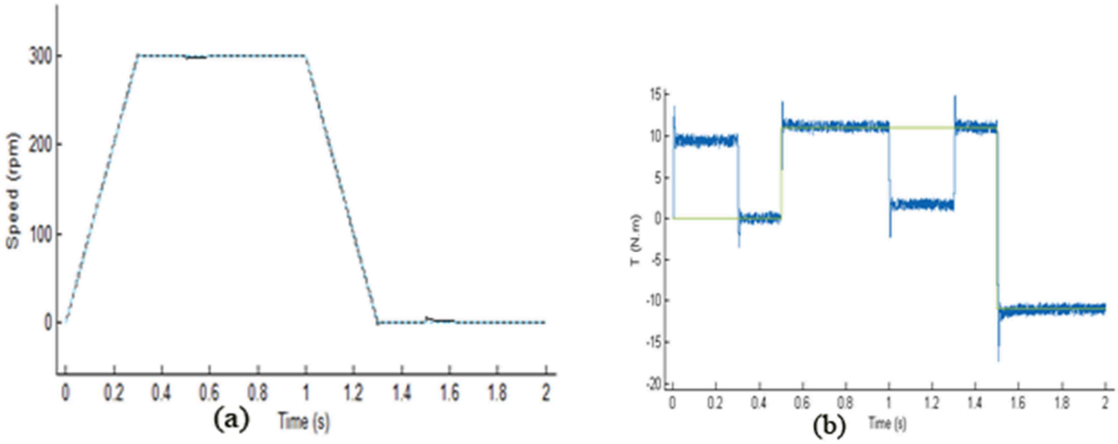

Fig. 4.Effects of Stator Resistance (R_s), (a): Motor speed and speed reference
(b): Electromagnetic torque and reference torque

Conclusion

This paper proposed a new MRAS speed observer for high-performance vector controlled of induction motor drives using a novel neural networks based speed estimator. Structure and algorithm were simple. The simulation showed that proposed control strategy could identify and track the motor speed accurately during the whole operating region. Overall, the dynamic response of this scheme of speed estimation showed a good performance. Finally, analysis of the performance of the speed estimator during the changes of the stator resistance was presented which showed the speed estimator was robust to changes in motor parameters.

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