On-Line Neural Network Stator Resistance Estimation in Direct Torque Controlled Induction Motor Drive

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***Abstract*—This paper presents an on-line estimation for the stator resistances of the induction motor in the direct torque controlled drive, using artificial neural networks. The variation of stator resistance due to changes in temperature or frequency degrades the performance of such control strategy. In order to solve this issue, a backpropagation algorithm is used for training of the neural network. The error between the desired state variable of an induction motor and the actual state variable of a neural model is back propagated to adjust the weights of the neural model, so that the actual state variable tracks the desired value. Simulation results show the good performance of these resistance estimator and torque response of the drive.**

Neural network; estimator; DTC; Induction motor

I. INTRODUCTION

High performance torque controlled induction machine drives can be achieved when the proper control scheme utilizes accurate estimated flux. The stator resistance changes due to the temperature variations and stator frequency variation that deteriorate the drive performance by introducing errors in the estimated magnitude and position of the stator flux vector. This in turn affects the estimation of the electromagnetic torque and degrades the performance of the DTC system. At low speed, this effect is important and if the value of the stator resistance which is used in controller is less than its actual value, the developed flux and torque will he decreased. Using greater value of the stator resistance in controller than its real value leads to instability [1].

Several methods have been reported to minimize the consequences of parameter sensitivity in direct torque control drives. The stator resistance tuning has been proposed using hybrid flux estimation [2][3]. The hybrid flux estimation utilizes a combined model which has smooth transition from the stator voltage to the rotor voltage based flux estimations from low speeds to high speeds, and vice versa. In [4],[5], the stator resistance is calculated by means of dc components of the voltage and current measurements. Online identification has been developed using model reference adaptation [6].

It is also possible to synthesize the tuning of stator resistance using intelligent control technique. For instance, [7] proposed Fuzzy estimator which employs stator current phasor error to adjust the stator resistance. It has been shown that, among the other variables of the machine, the stator current is highly affected by the resistance changes.

In this paper, the effect of stator resistance variation is discussed and the stator resistance is estimated using an on-line neural network estimator. The performance of the control drive is examined by extensive simulation studies.

II. DTC PRINCIPLE

Takahachi, Depenbrock [3]-[8] proposed a high performance scalar control method which is popularly known as direct self control (DSC) or direct torque control (DTC). The structure of a classical DTC scheme is illustrated in Fig. 1. Classical DTC selects one of the six voltage vectors and two zero voltage vectors generated by a VSI in order to keep stator flux and torque within the limits of two hysteresis bands. The right application of this principle allows a decoupled control of flux and torque without the need of coordinate transformations, PWM pulse generation and current regulators [8]. However, the presence of hysteresis controllers leads to a non-constant switching frequency operation.

The basic DTC strategy is that the status of the errors of stator flux magnitude $|\overline{\psi}_s|$ and electromechanical torque (Tem) can be detected and digitalized by two- and three-level hysteresis comparators. The optimum switching table (Table 1) is then used to calculate the status of three switches S1, S2, S3, that will determine the location of the voltage space vector $\overline{V}_s$ which depends on the stator flux's angle (θ_s).

The stator flux, as given in (1), can be approximated by (2) over a short time period if the stator resistance is ignored.

$$\overline{\psi}_s = \overline{\psi}_{so} + \int_0^t (\overline{V}_s - R_s \bar{I}_s)dt \qquad (1)$$

$$\overline{\psi}_s \approx \overline{\psi}_{so} + \int_0^t \overline{V}_s dt \qquad (2)$$

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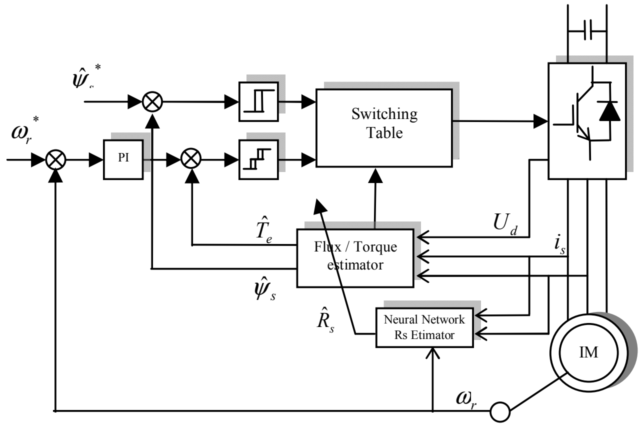

Figure 1. DTC principle

During one period of sampling T_s, the voltage vector applied to the machine remains constant, and thus we can write:

$$\overline{\psi}_s(k+1) \approx \overline{\psi}_s(k) + \overline{V}_s.T_s \Rightarrow \Delta\overline{\psi}_s \approx \overline{V}_s.T_s \tag{3}$$

Because the rotor time constant is larger than the stator one, the rotor flux changes slowly compared to the stator flux. Thus torque can be controlled by quickly varying the stator flux position by means of the stator voltage applied to the motor.

TABLE I. SWITCHING STATES

Δψs	ΔTe	S1	S2	S3	S4	S5	S6
1	1	110	010	011	001	101	100
	0	000	000	000	000	000	000
	-1	101	100	110	010	011	001
0	1	010	011	001	101	100	110
	0	000	000	000	000	000	000
	-1	001	101	100	110	010	011

At any instant, the torque is proportional to the stator flux magnitude, the rotor flux magnitude, and the sinus of the angle δ (see Fig.2). It is expressed by:

$$T_e = k(\overline{\Psi}_s \times \overline{\Psi}_r) = k|\Psi_s||\Psi_r|\sin(\delta) \tag{4}$$

Where: $k = \dfrac{3P}{2}\dfrac{L_m}{\sigma L_s L_r}$ and $\sigma = 1 - \dfrac{L_m{}^2}{L_s L_r}$

The estimated electromagnetic torque can be expressed as:

$$T_e = \frac{3P}{2}(\psi_{s\alpha} i_{s\beta} - \psi_{s\beta} i_{s\alpha}) \tag{5}$$

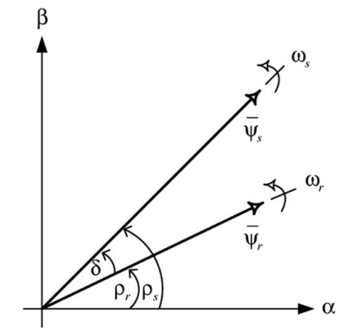

Figure 2. Stator and rotor flux vectors

III. NEURAL NETWORK STATOR RESISTANCE ESTIMATOR

The stator resistance of an induction motor can be estimated with the adaptive estimator using neural networks as illustrated in Fig. 3.

Two independent observers are used to estimate the rotor flux vectors of the induction motor. Equation (6) is referred to as "voltage model" which is based on measured stator voltages and stator currents from the induction motor. Equation (7) is referred to as "current model", which uses the measured stator currents and rotor speed.

$$\begin{aligned} \frac{d\psi_{r\alpha}}{dt} &= \frac{L_r}{L_m}\left(V_{s\alpha} - R_s i_{s\alpha} - \sigma L_s \frac{di_{s\alpha}}{dt}\right) \\ \frac{d\psi_{r\beta}}{dt} &= \frac{L_r}{L_m}\left(V_{s\beta} - R_s i_{s\beta} - \sigma L_s \frac{di_{s\beta}}{dt}\right) \end{aligned} \tag{6}$$

$$\begin{aligned} \frac{d\hat{\psi}_{r\alpha}}{dt} &= \frac{1}{T_r}\left(L_m i_{s\alpha} - \hat{\psi}_{r\alpha} - \omega_r T_r \hat{\psi}_{r\beta}\right) \\ \frac{d\hat{\psi}_{r\beta}}{dt} &= \frac{1}{T_r}\left(L_m i_{s\beta} - \hat{\psi}_{r\beta} + \omega_r T_r \hat{\psi}_{r\alpha}\right) \end{aligned} \tag{7}$$

Using the discrete form of equation (7), the new α –axis current equation can be discretized and written as:

$$\begin{aligned} i_{s\alpha}{}^*(k) = w_1 i_{s\alpha}{}^*(k-1) + w_2\psi_{r\alpha}(k) + w_3\omega_r\psi_{r\beta}(k) \\ + w_4 V_{s\alpha}(k) \end{aligned} \tag{8}$$

Where, $w_1 = 1 + \dfrac{T_s}{\sigma L_s}\dfrac{L_m{}^2}{L_r T_r} + \dfrac{T_s}{\sigma L_s}R_s$; $w_2 = \dfrac{T_s}{\sigma L_s}\dfrac{L_m}{L_r T_r}$

$w_3 = \dfrac{T_s}{\sigma L_s}\dfrac{L_m}{L_r}\omega_r$; $w_4 = \dfrac{T_s}{\sigma L_s}$

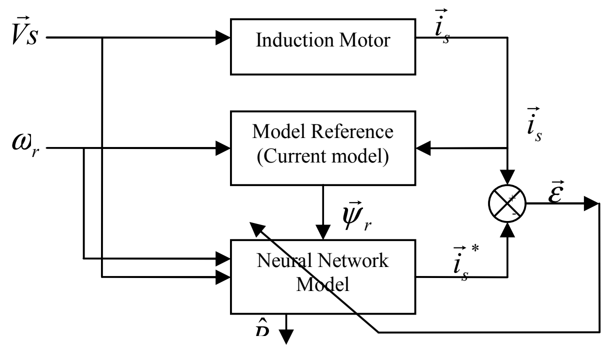

Figure 3. Rs estimation using Neural Network

The weights w_2, w_3, and w_4 are considered constant and calculated from the motor parameters, motor speed ω_r and the sampling interval Ts. The weight between the neurons, w1 contains the stator resistance term, therefore, it is trained so as to minimize the energy function E.

$$E = \frac{1}{2}\vec{\varepsilon}^{\,2}(k) = \frac{1}{2}\left\{i_{s\alpha}(k) - i^*_{s\alpha}(k)\right\}^2 \tag{9}$$

The weight variation for w1 is given by:

$$\Delta w_1(k) = \left[i_{s\alpha}(k) - i^*_{s\alpha}(k)\right] i^*_{s\alpha}(k-1) \tag{10}$$

Equation (8) can be represented by a recurrent neural network as shown in Fig. 4.

To accelerate the convergence of the error back propagation learning algorithm, the current weight adjustment is supplemented with a fraction of the recent weight adjustment, as in equation (11).

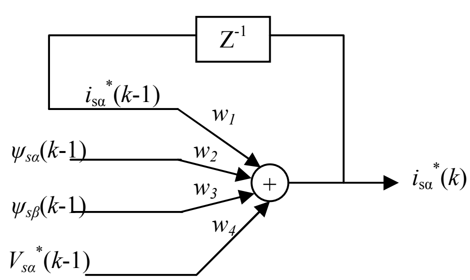

Figure 4. stator current estimation based on recurrent network

$$w_1(k) = w_1(k-1) + \eta\Delta w_1(k) + \alpha\Delta w_1(k-1) \tag{11}$$

where η is the training coefficient, α is a user selected positive momentum constant.

The stator resistance can be calculated from (12).

$$\hat{R}_s = \left\{ w_1 - 1 - \frac{T_s}{\sigma L_s}\frac{L_m^{\,2}}{L_r T_r} \right\} \frac{\sigma L_s}{T_s} \tag{12}$$

IV. SIMULATION RESULTS

The performance of the proposed ANN stator resistance estimator is verified by simulation of the test drive model built in Matlab/Simulink ® environnement. The system's response with and without the resistance estimator are compared. The induction motor parameters are listed in Table.2.

The speed loop control is based on PI regulator witch give the corresponding torque reference for the drive. While the stator flux reference is equal to 0.8 Wb.

The drive has been tested particulary in low speed region at 20 rad/s witch is the most critical region for stator resistance detuning.

A step variation (64% drop) of the stator resistance is introduced at 0.5 sec. Fig. 5, shows that the system becomes unstable when estimated stator resistance is higher than its actual value. The reason of the instability of the system is due to the opposite effects between the controller and the motor [1]. The increased current (Fig 5.b) due to lower actual stator resistance value, causes increased stator resistance voltage drops in the estimator resulting in lower estimation of the flux linkages and electromagnetic torque estimations. This value of the stator current leads ti high torque oscillation (Fig 5.d) and instability of the speed control loop (Fig 5.c). Also the stator flux locus is affected giving much more ripples around the desired stator flux (Fig 5.e-f).

Since the switching action is strongly affected by the torque controller, the accurate estimation of the torque is important for high performance and proper control in DTC. The accurate of stator flux estimation is mandatory in estimating the torque.

TABLE II. INDUCTION MOTOR PARAMETERS

Rated power Prated [KW]	3
Rtaed Vltage Urated [V]	220
Rated frequency [Hz]	50
Pole-pair	2
Stator resistance Rs [Ω]	2.2
Rotor resistance Rr [Ω]	2.68
Stator inductor Ls[mH]	229
Rotor resistance Lr[mH]	229
Phase magnelizing inductance 1m, [mH]	217
Rated speed [rpm]	1440

From the wave forms of fig.6, it can be seen that the estimated stator resistance tracks the actual resistance very closely. The stator current remains constant (Fig 6.b). The electromagnetic torque and stator flux module (Fig 6.d-e)exhibit acceptable ripples due to the effectiveness of the control strategy.

V. CONCLUSION

To increase the performance of the DTC system due to changes in stator resistance, stator resistance neural network adaptive system is considered. This method is based on comparing the actual stator flux with the neural network adaptive model trained online by a backpropagation algorithm.

The simulation results are used to study the performances of the drive system particularly at low speed. This study reveals that, the system becomes stable with a good accuracy of stator resistance estimation.

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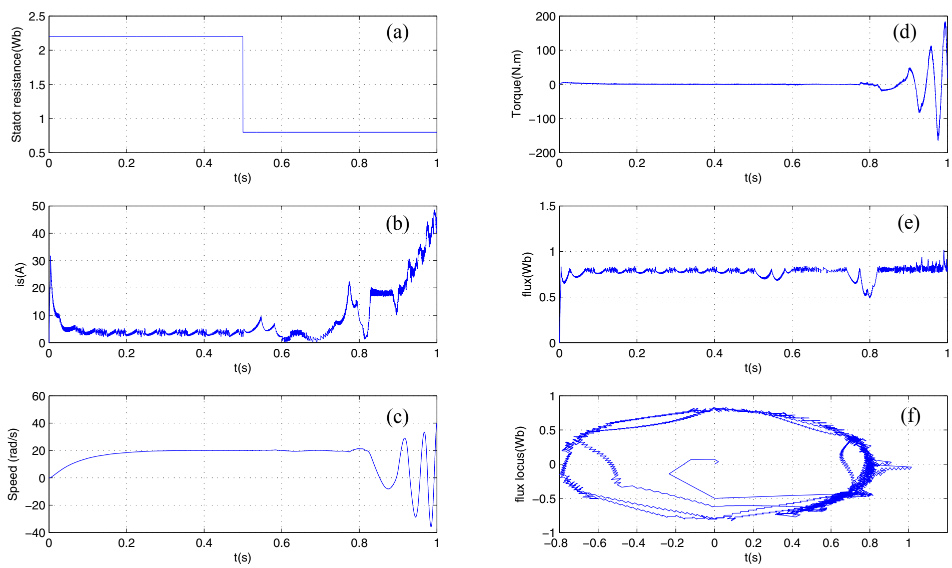

Figure 5. effect of stator resistance variation. (a) stator resistance step variation, (b) stator current module (A), (c) speed (rad/s), (d) electromagnetic torque (N.m), (e) stator flux module (Wb), (f) stator flux locus

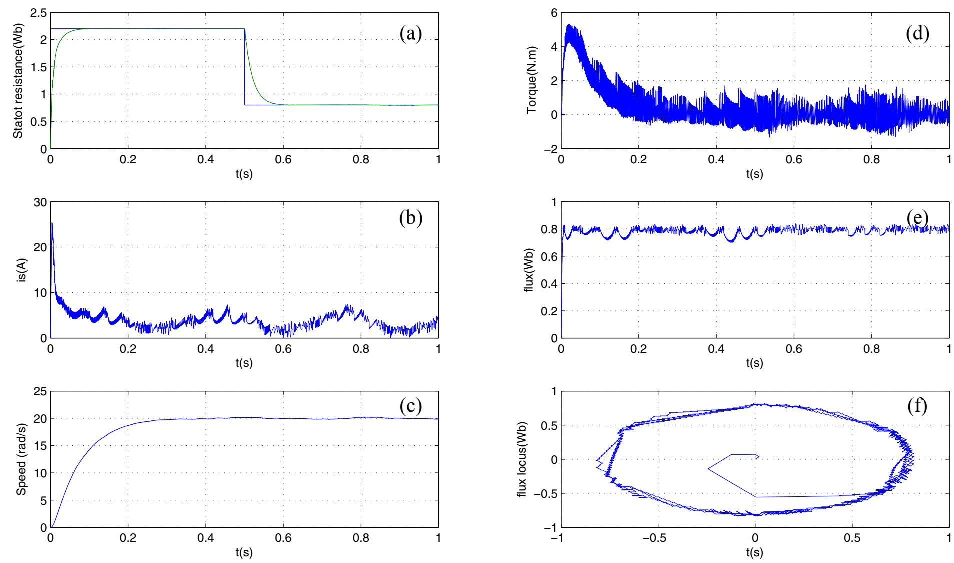

Figure 6. Stator resistance compensation. (a) stator resistance step variation, (b) stator current module (A), (c) speed (rad/s), (d) electromagnetic torque (N.m), (e) stator flux module (Wb), (f) stator flux locus