Offline Artificial Neural Network Rotor Flux Estimator for Induction Motor

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***Abstract*— Rotor flux is an important parameter in field-oriented control of induction motor (IM). It can be obtained through direct physical measurement at the air-gap or indirectly by using estimators. In this paper, the feedforward Artificial Neural Network (ANN) model for rotor flux estimation is proposed and analyzed. The network is trained using equivalent circuit model data and the Levenberg-Marquardt algorithm. The result shows that the proposed ANN rotor flux estimator is able to perform IM rotor flux estimation with 2.99e-05 MSE.**

Index Terms— Induction motor rotor flux estimator, artificial neural network estimator, Levenberg-Marquardt algorithm

I. Introduction

Induction motor (IM) rotor flux observer (FO) has a key role in field-oriented-control (FOC) of IM-drives (See Fig. 1). Due to the insufficient clearance at the air-gap for sensor mounting, observer model is often utilized for rotor flux estimation. This rotor flux angle and magnitude are used as the input for *d-q* transformation module in the control loop of mechanical variables such as the shaft position, speed and torque.

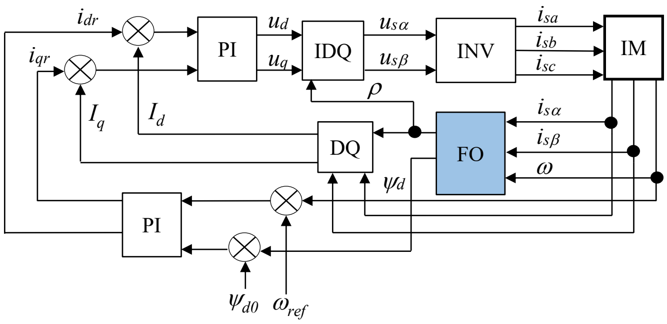

Fig. 1. Flux observer (FO) implementation in FOC

To understand the problems in the implementation, we consider the two-component Verghese-Sanders flux estimation [1] equations as shown in (1). The motor parameters (R_S, R_R, L_S, L_R, L_M), the number of pole pairs (n_p) and total leakage factor ($\sigma = 1 - \frac{L_M^2}{L_S L_R}$) are obtained from the manufacturer datasheets or by performing motor testing for parameters extraction. The error dynamics model is obtained by evaluating the discrepancy of the estimator output to the actual value which is calculated using motor mathematical model. Selected estimator gain (κ) is tuned so that the error dynamics converge to zero. Lyapunov theorem is used to evaluate the stability of the estimator [2], [3].

Referring to (1), the $\hat{\psi}_R$ can be solved by integrating forward the equation in real-time from a specific initial condition. This means that measurement value of i_s, v_s and ω should be accurate as well as the motor parameters must remain certain. This makes the estimator become highly vulnerable from measurement error and motor parameters uncertainties.

$$\begin{aligned}\hat{\psi}_{R\alpha} &= \frac{1}{1-\kappa\frac{L_M}{L_R}}\Big(-\frac{R_R}{L_R}\hat{\psi}_{R\alpha} - n_p\omega\hat{\psi}_{R\beta} + \frac{L_M R_R}{L_R}i_{S\alpha} \\ &\qquad + \kappa\big(R_s i_{S\alpha} + \sigma L_s\frac{di_{S\alpha}}{dt} - v_{S\alpha}\big)\Big) \\ \hat{\psi}_{R\beta} &= \frac{1}{1-\kappa\frac{L_M}{L_R}}\Big(-\frac{R_R}{L_R}\hat{\psi}_{R\beta} - n_p\omega\hat{\psi}_{R\alpha} + \frac{L_M R_R}{L_R}i_{S\beta} \\ &\qquad + \kappa\big(R_s i_{S\beta} + \sigma L_s\frac{di_{S\beta}}{dt} - v_{S\beta}\big)\Big)\end{aligned} \tag{1}$$

There are many reported works have been done for improving estimation accuracy and to establish adaptive motor parameters identification. However, these increase computation burden and hence would left out the issues of computational latency [4], [5].

II. Rotor Flux Model

The most widely used model in control system are developed based on equivalent circuit such presented in the work of Slemon [6] and Susca et. al. [7]. In many cases the linear T-form circuit are usually utilized. Fig. 2 (b) illustrates an example of T-Form cage-IM model. This model is used in the Simulink's IM block. For magnetically linear machine, the relationship of the flux (Φ) is proportional to the product of inductance (L) and current (i). Therefore, the rotor fictitious flux (ψ) can be simplified to (2).

For cage-IM where the rotor variables are not available for measurement, the rotor current are estimated from the stator variables. The estimation is calculated using mathematical model of the IM. Fig. 2. (Left) illustrates the sketch of cage-IM showing that there is no direct electrical link between the stator and rotor. The gap between the stator and rotor are typically less than 2mm which makes sensor mounting for direct measurement is very challenging for practical application. Fig. 2 (Right) showing the relationship between the *a-b-c*, *α-β*, and *d-q* frames. This relationship is important in defining the rotor variables in stator variables. Equation (3) shows the rotor flux which defined by the *d*-component of the rotating *d-q* frame in the *α-β* stationary reference frame.

$$\begin{aligned}\psi_{qs} &= L_s i_{qs} + L_m i_{qr} \\ \psi_{ds} &= L_s i_{ds} + L_m i_{dr} \\ \psi_{qr} &= L_r i_{qr} + L_m i_{qs} \\ \psi_{dr} &= L_r i_{dr} + L_m i_{ds}\end{aligned} \tag{2}$$

$$\begin{aligned}\rho &= \tan^{-1}\frac{\psi_{d\alpha}}{\psi_{d\beta}} \\ \psi_r &= \sqrt{\psi_{d\alpha}^2 + \psi_{d\beta}^2}\end{aligned} \tag{3}$$

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