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Experimental Evaluation of Torque Performance of Voltage and Current Models using Measured Torque for Induction Motor Drives

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ABSTRACT

In this paper, two kinds of observers are proposed to investigate torque estimation. The first one is based on a voltage model represented with a low-pass filter (LPF); which is normally used as a replacement for a pure integrator to avoid integration drift problem due to dc offset or measurement error. The second estimator used is an extended Kalman filter (EKF) as a current model, which puts into account all noise problems. Both estimation algorithms are investigated during the steady and transient states, tested under light load, and then compared with the measured mechanical torque. In all conditions, it will be shown that the torque estimation error for EKF has remained within narrower error band and yielded minimum torque ripples when compared to LPF estimation. This motivates the use of EKF observer in high performance control drives of induction machines for achieving improved torque response.

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1. INTRODUCTION

Most real world applications need accurate speed and torque estimations in order to avoid improper operation and to achieve high stablity. When designing an observer for an electrical drive system, two kinds of estimation methods have been investigated to date which are based on the voltage model (VM), or the current model (CM). The VM is known for a stator flux estimator used in sensorless induction motor (IM) drives since the rotor speed information is not required for the stator flux estimation, and the only imporatnt variable of the observer is the stator resistance [1]. VM is normally used in high speed applications, since at low speed, some problems are encountered. Thus, two recognized problems are associatied with VM since a pure integrator is used: The first one is a drift and saturation in the estimated flux due to the presence of the DC offset in the measured current [1-2], and the second problem is the extreme sensitivity to stator resistance mismatch due to temperature increase, particularly at low speed when the stator voltage is low [2]. Several solutions to these problems have been proposed. For the drift problem, a low-pass filter (LPF) is normally used in place of a pure integrator. However, this method reduces the performance of the system drive because of the phase and magnitude errors due to the LPF, especially when frequencies are close to the cutoff frequency [3]. In an attempt to solve this problem, Karanayil et. al. [4] have addressed small-time-constant cascaded LPFs to decrease the DC offset decay time. Comanescu and Longya [5] have presented flux estimation based on a phase locked loop (PLL) programmable LPF depicting an enhancment in the phase and magnitude of the estimated flux. Online adaptation of the stator resistance is additionally important to enhance the performance of the VM at low frequency range. To solve this drawback, [6] has proposed a simultaneous estimation of rotor and stator resistances using extended Kalman filter (EKF).

Alternatively, CM estimation, on the other hand, is suitable to be applied at very low frequency, and requires information on d and q stator current and speed [2], [7]. In real time applications, accurate speed measurement is important for robust and precise control of IMs. However, the use of a speed sensor to get the speed or position of the rotor is not favored as it decreases the reliability and robustness of the motor control, and increases hardware complexity and cost [8]. Thus, speed estimation techniques based on terminal variables that can replace mechanical speed sensors, have received increasing attention in recent decades. It is well-known that even though the use of CM has managed to remove the sensitivity to the stator resistor variation at low speed, it has introduced parameter-sensitivity due to the rotor parameter variations, especially at high speed region. To address this problem, various methods have been proposed. For instance, Salmasi and Najafabadi [9] have addressed an adaptive observer which is capable of concurrent estimation of stator currents and rotor fluxes with online adaptation of rotor and stator resistances. Toliyat et al.[10] have developed artificial neural networks (ANNs) in closed loop observer for estimating rotor resistance and mutual inductance. There is also a stochastic approach that uses EKF in estimating the variables of IM, such as speed, torque, and flux [11]-[14]. Using EKF-based observer, it is possible to estimate the unknown parameters of IM, taking into account the parameter variations and measurement noises, in a relatively short time interval [15]-[16].

The main contribution of this paper is to evaluate the torque performance for both LPF and EKF observers under the same conditions. Unlike previous studies, where the emphasis is only on speed, rotor flux, stator flux, or motor parameters, this paper focuses on investigation of the torque behavior based on both observers during the steady and transient states, and then compared with the measured mechanical torque. The paper is organized in five sections. The following section presents the EKF-based torque calculation. Section three deals with the low pass filter, which represents the voltage model. Experimental results and discussion are presented in Section four. Finally, section five concludes the work.

2. EXTENTDED KALMAN FILTER ALGORITHM

In this study, EKF is used to concurrently estimate current, rotor flux, and rotor speed for speed sensorless control of IMs. However, the precise estimation of these state variables is very much reliant on how well the filter matrices are selected over a wide speed range [17]. The extended model to be used in the development of the EKF algorithm can be written in the following general form (as referred to the stator stationary frame.

$$\dot{x}_i(t) = f_i(x_i(t), u(t)) + w_i(t) \tag{1}$$

$$f_i(x_i(t), u(t)) = A_i(x_i(t))x_i(t) + Bu(t) \tag{2}$$

$$Y(t) = H_i(x_i(t))x_i(t) + Bu(t) + v_i(t) \tag{3}$$

There i = 1, 2, extended state vector x_i is representing the estimated states, f_i is the nonlinear function of the states and inputs, A_i is the system matrix, u is the control-input vector, B is the input matrix, w_i is the process noise, H is the measurement matrix, and v_i is the measurement noise. The general form of IM can be represented by (4) and (5).

$$\underbrace{\begin{bmatrix} \dot{i}_{sd} \\ \dot{i}_{sq} \\ \dot{\psi}_{rd} \\ \dot{\psi}_{rq} \\ \dot{\omega}_r \end{bmatrix}}_{\dot{X}} = \underbrace{\begin{bmatrix} -\left(\frac{R_s}{L_\sigma} + \frac{L_m^2 R_r}{L_\sigma L_r^2}\right) & 0 & \frac{L_m R_r}{L_\sigma L_r^2} & \frac{\omega_r L_m}{L_\sigma L_r} & 0 \\ 0 & -\left(\frac{R_s}{L_\sigma} + \frac{L_m^2 R_r}{L_\sigma L_r^2}\right) & -\frac{\omega_r L_m}{L_\sigma L_r} & \frac{L_m R_r}{L_\sigma L_r^2} & 0 \\ \frac{R_r}{L_r} & 0 & -\frac{R_r}{L_r} & -\omega_r & 0 \\ 0 & \frac{R_r}{L_r} L_m & \omega_r & -\frac{R_r}{L_r} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}}_{A} \cdot \underbrace{\begin{bmatrix} i_{sd} \\ i_{sq} \\ \psi_{rd} \\ \psi_{rq} \\ \omega_r \end{bmatrix}}_{X} + \underbrace{\begin{bmatrix} 1/L_\sigma & 0 \\ 0 & 1/L_\sigma \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}}_{B} \cdot \underbrace{\begin{bmatrix} v_{sd} \\ v_{sq} \end{bmatrix}}_{u} + w(t) \tag{4}$$

$$\begin{bmatrix} i_{sd} \\ i_{sq} \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}}_{H} . \underbrace{\begin{bmatrix} i_{sd} \\ i_{sq} \\ \psi_{rd} \\ \psi_{rq} \\ \omega_r \end{bmatrix}}_{X} + v(t) \tag{5}$$

Where i_{sd} and i_{sq} are the d and q components of stator current, Ψ_{rd} and Ψ_{rq} are d-q rotor flux components, ω_r is the rotor electric angular speed in rad/s, vsd and vsq are the stator voltage components, L_s, L_r and L_m are the stator, rotor and mutual inductances respectively, R_s is the stator resistance, and R_r is the rotor resistance.

In this section, the EKF algorithm used in the IM model will be derived using the extended model in (4) and (5). For nonlinear problems, such as the one in consideration, the KF method is not strictly applicable, since linearity plays an important role in its derivation and performance as an optimal filter. The EKF technique attempts to overcome this difficulty by using a linearized approximation, where the linearization is performed about the current state estimate. This process requires the discretization of (4) and (5) as follows:

$$\dot{x}_i(k+1) = f_i(x_i(k), u(k)) + w_i(k) \tag{6}$$

$$f_i(x_i(k), u(k)) = A_i(x_i(k))x_i(k) + Bu(k) \tag{7}$$

$$Y(k) = H_i(x_i(k))x_i(k) + Bu(k) + v_i(k) \tag{8}$$

The linearization of (7) is performed around the current estimated state vector $\hat{x}_i$ given as follows:

$$F_i(k) = \left. \frac{\partial f_i(x_i(k), u(k))}{\partial x_i(k)} \right|_{\hat{x}_i(k)} \tag{9}$$

The resulting EKF algorithm can be presented with the following recursive relations:

$$P(k) = F(k)P(k)F(k)^{-1} + Q \tag{10}$$

$$K(k+1) = H^T P(k)(HP(k+1)H^T + R)^{-1} \tag{11}$$

$$\hat{x}(k+1) = \hat{f}(x(k), u(k)) + K(k)(Y(k) - H\hat{x}(k)) \tag{12}$$

$$P(k+1) = (I - K(k+1)H)P(k) \tag{13}$$

In (10)-(13) Q is the covariance matrix of the system noise, namely, model error, R is the covariance matrix of the output noise, namely, measurement noise, and P are the covariance matrix of state estimation error. The algorithm involves two main stages: prediction and filtering. In the prediction stage, the next predicted states $\hat{f}(\cdot)$ and predicted state-error covariance matrices, $\hat{P}(\cdot)$ are processed, while in the filtering stage, the next estimated states $\hat{x}(k+1)$ obtained as the sum of the next predicted states and the correction term [second term in (12)], are calculated. The structure of the EKF algorithm is shown in Figure 1.

The electromagnetic torque based on EKF is expressed based on the selected state variables which are the stator current and rotor fluxr:

$$T_e = \frac{3}{2}\frac{p}{2}\frac{L_m}{L_r}\left(i_{sq}\psi_{dr} - i_{sd}\psi_{qr}\right) \tag{14}$$

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3. VOLTAGE-MODEL-BASED TORQUE ESTIMATOR

The stator flux estimation based on the voltage model is derived from the stator voltage equation given by:

$$\bar{v}_s = R_s i_s + \frac{d\bar{\psi}_s}{dt}.$$

From this equation, three components are known, i.e., the vector voltage, stator resistor, and measured current. The only missing variable is the stator flux. Therefore, the stator flux can be written as:

$$\bar{\psi}_s = \int \left(\bar{v}_s - \bar{i}_s R_s\right) dt. \qquad (15)$$

In practice, the pure integrator used in estimating the stator flux is often substituted with a low pass filter to avoid the integration drift problem due to the dc offset or measurement noise. However, there should be a proper selection for the cutoff frequency used in LPF. While it is good to set the cutoff frequency as low as possible so that the phase and magnitude errors are minimized, it must be noted that this will reduce the effectiveness of the LP-filter-based estimator to filter out the DC offset which is likely present in the sensed currents or voltages. Selecting a cutoff frequency which is closer to the operating frequency will reduce the dc offset in the estimated stator flux, which on the other hand will introduce phase and magnitude errors. In order to use the low pass filter, (16) should be under sinusoidal steady-state condition, which can be written in the following form:

$$j\omega_e \bar{\psi}_S = \bar{v}_S - \bar{i}_S R_S.$$
$$\bar{\psi}_s = \frac{\bar{v}_s - \bar{i}_s R_s}{j\omega_e}. \qquad (16)$$

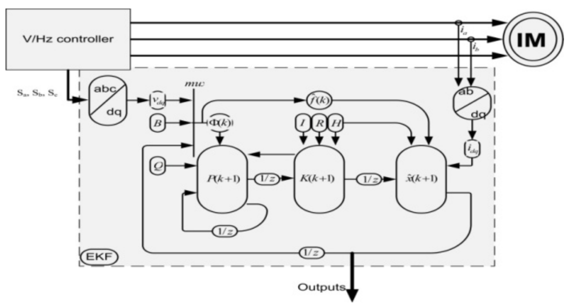


Figure 1. Structure of extended Kalman filter

With adding the cutoff frequency to (17), the LPF becomes:

$$\bar{\psi}'_s = \frac{\bar{v}_s - \bar{i}_s R_s}{j\omega_e + \omega_c}. \qquad (17)$$

Where ω_c is the cutoff frequency of the LP filter in radians per second, ω_e is the synchronous angular frequency and is the estimated stator flux. Equation (16) and (17) clearly indicated that under steady-state condition (and obviously transient states), there will be differences in the magnitude and phase between the pure integrator and LPF based estimation.

Hence, the electromagnetic torque equation for LPF is calculated based on the estimated stator flux and measured stator current as given by (18). The error in the stator flux estimation will obviously be reflected in the torque estimation.

$$T_e = \frac{3}{2}\frac{p}{2}\left(\overline{\psi}'_{sd} i_{sq} - \overline{\psi}'_{sq} i_{sd}\right) \tag{18}$$

4. EXPERIMENTAL RESULTS AND DISCUSSION

In order to study the performance and feasibility of the estimators, experimental results acquired from both the EKF and LPF-based estimators are compared with the measured results obtained using electrical torque transducer (TM308) from Magtrol and rated at 20 N.m. The experimental set-up also consists of an insulated-gate bipolar transistor inverter, a dSPACE 1104 controller card, and a 1.5-kW 4-pole squirrel-cage induction motor. The load is generated through a hysteresis brake by Magtrol and controlled through a proportional amplifier. The parameters of the induction motor used in the experiment are as shown in Table 1. An incremental encoder with 1024 ppr is used to measure the rotor speed, which is sampled every 2 ms. For safety reason, the DC voltage is limited to 200V, which means that the based speed is reduced to 55 rad/s. The main task of the dSPACE is to generate the PWM control signals using the constant V/Hz scheme. The task of FPGA is to generate the blanking time. The sampling period of the constant V/Hz scheme, including the state estimators, is 100μs. The full schematic of the experimental setup can be seen in Figure 2.

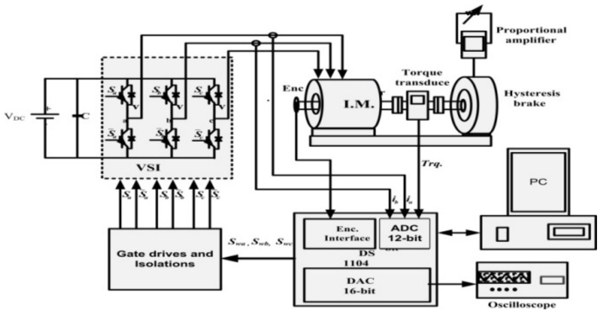


Figure 2. Schematic representation of the experimental setup

With assumption of white noise, the state estimation error matrix *P* is initiated with the diagonal matrix one, whereas the initial values of filters in the EKF algorithm are found by using the GA algorithm in [18] but with optimizing only two covariance filters; *R* and *Q* . This is to achieve a rapid initial convergence as well as the desired transient- and steady-state performance. Thus, the initial values for EKF scheme can be defined underneath:

$$P = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$Q = \begin{bmatrix} 8.47*10^{\wedge}\text{-}14 & 0 & 0 & 0 & 0 \\ 0 & 2.38*10^{\wedge}\text{-}6 & 0 & 0 & 0 \\ 0 & 0 & 3.60*10^{\wedge}\text{-}13 & 0 & 0 \\ 0 & 0 & 0 & 1.0*10^{\wedge}\text{-}16 & 0 \\ 0 & 0 & 0 & 0 & 1.62*10^{\wedge}\text{-}5 \end{bmatrix}$$

$$R = \begin{bmatrix} 0.0053 & 0 \\ 0 & 1.62*10^{\wedge}\text{-}5 \end{bmatrix}$$

As for LPF, the estimated stator flux is based on the cutoff frequency set to 5rad/s. The constant V/Hz drive is run in an open loop mode where a step change in the speed reference from 0 to 55rad/s is applied. The controller algorithm is auto-generated through SIMULINK, and is applied in real-time via dSPCE controldesk on a windows based PC. The two phases of current are measured using Hall Effect current sensors and sent to analog digital conversion (ADC) channels of dSPCE interface, whereas the d-q voltage vectors, shown in Figure 3, are directly calculated based on the control signals obtained from the controller as follows.

$$v_{sd} = \frac{1}{3}V_{DC}(2S_a - S_b - S_c) \tag{19}$$

$$v_{sq} = \frac{1}{\sqrt{3}}V_{DC}(S_b - S_c) \tag{20}$$

Table 1. Induction Motor Parameters

***Rs* [Ω]**	***Rr* [Ω]**	***Ls* [H]**	***Lr* [H]**	***Lm* [H]**	***JL* [Kg. m²]**	***F***
3	4.1	0.3419	0.3513	0.324	0.00952	4

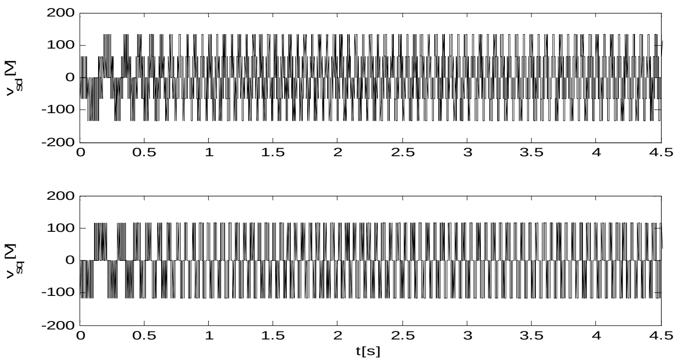
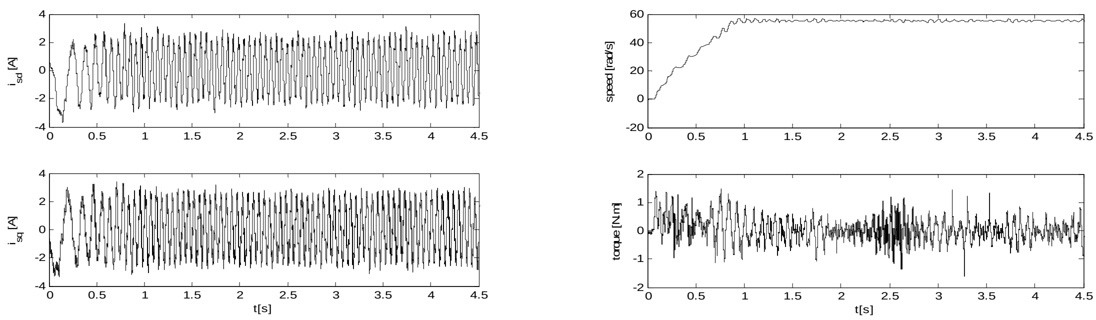


Figure 3. The d-q input voltage for constant V/Hz controller

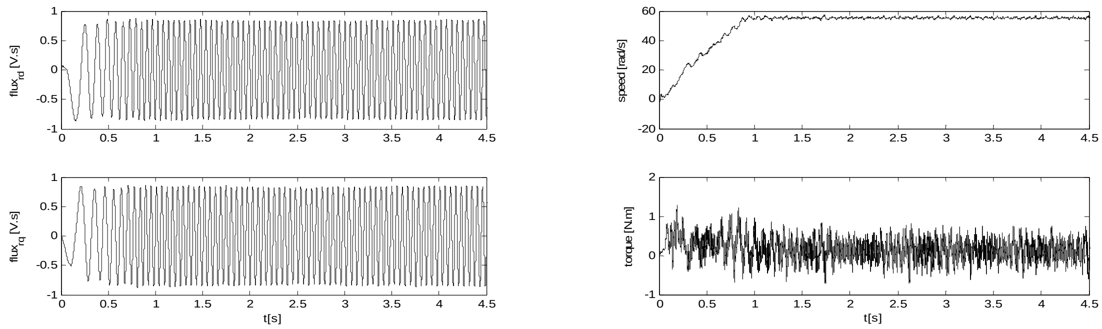
Figure 4 shows the results obtained from experimental constant V/Hz controller; i.e. d-q stator currents, speed, and torque. The performance of the EKF algorithm is evaluated experimentally through the estimated speed and the calculated torques as shown in Figure 5. In order to further examine the differences between the measured and calculated torque based on EKF estimator, the zoomed waveforms will be shown latetr in the discussion. The EKF not only can be used to estimate the torque, but also can be utilized to estimate the speed; the estimated speed based on EKF and measured speed obtained from V/Hz controller is shown in Figure 5(b).



(a) (b)

Figure 4. Measured results for constant V/Hz controller: (a) d-q stator current, (b) measured speed and torque

The experimental results of the d-q axes of the estimated stator flux, and the calculated torque based on the LPF voltage model is shown in Figure 6. Examining Figure 7(a) and (b), one can clearly see the superior performance of the EKF-based torque calculation over the voltage model based estimator through the error bands (the difference between the measured and estimated values).



(a) (b)

Figure 5. Experimental results for EKF observer with no load: (a) d-q rotor flux, (b) estimated speed, and estimated torque

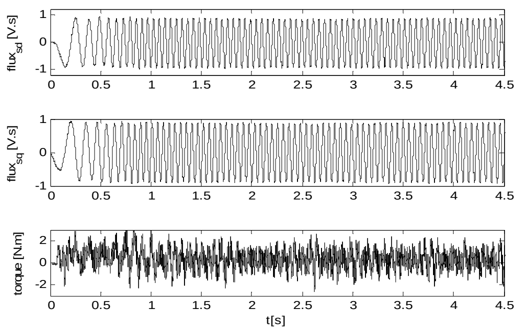
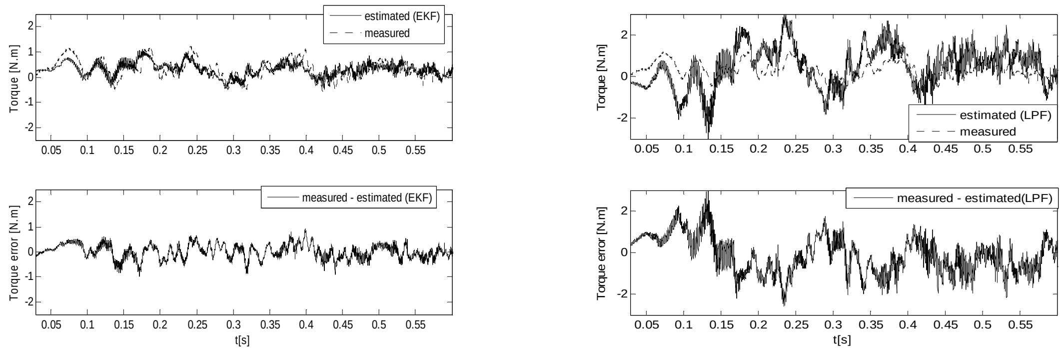


Figure 6. Experimental results of d-q stator flux and estimated torque for LPF estimator with no load



(a) (b)

Figure 7. Comparison between the measured torque and estimated torque obtained from (a) EKF and (b) LPF during transient state

4. CONCLUSION

In this paper, a comparison of state estimations for torque calculation based on EKF and LPF filters applied for an induction motor control has been performed. The performances of the EKF and LPF schemes under the same conditions are experimentally evaluated by comparing them with the results obtained from the measured values. It is revealed that the measured and estimated torques have similarities in terms of switching patterns. When comparing both results, the EKF-based state estimation shows much better accuracy than the LPF-based state estimation in calculating the torque. The EKF-based is also capable of estimating the speed under transient and steady state conditions within a smaller error band with minimum torque ripples. This motivates the use of the EKF estimation algorithm in high performance control drives of IMs.

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