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Estimation of Load Torque and Rotor Speed in Single-Phase Induction Motor Using EKF

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Abstract

This paper presents a novel method for estimation of load torque and rotor speed in single-phase Induction Motor (IM) with two asymmetrical windings by using Extended Kalman Filter (EKF). Normally, for estimation of load torque and rotor speed in IM, six state variables namely stator currents, rotor fluxes, rotor speed and load torque, are considered. This paper shows by considering five state variables, estimation of these parameters is possible. Simulation results show the good performance of the presented method.

Keywords: *EKF, estimation of load torque and rotor speed, single-phase IM, simulation results*

1. Introduction

Single-phase Induction Motors (IMs) can be known as the most popular motors which are widely applied in industrial and non-industrial applications. More ease access of single-phase AC grid than 3-phase AC grid can be considered as the advantage of single-phase IM. The advantages, popularity and its applications such as mixer, hair dryer, vacuum cleaner and etc. caused many researchers focused on this type of machine [1, 2].

One of the IM parameters which plays such important role in control of IM is rotor speed. Normally, the speed sensors can be used to make available control feedback in speed-controlled drives. The control scheme with speed sensor faced to some problems toward speed sensorless control scheme such as hardware complexity, lower reliability, bigger size and etc. Employing speed sensorless techniques in control of IMs would doubtless result in more economical electrical machine drives. Many researches have been carried out for sensorless control methods and particularly speed sensorless techniques for IM that can be operated in the wide speed range [3, 4]. Classification of speed sensorless techniques can be classified into two main categories, Model based methods and signal based methods. Model based methods are included of open loop [5-7], Extended Kalman Filter (EKF) [8-11], Luenberger [12], Sliding Mode Observer (SMO) [13-15], Model Reference Adaptive System (MRAS) [5], Neural Network (NN) [16-18] and signal based methods are included of saturation caused by main flux [19-21], rotor slot tracking [22-24], custom design [25].

EKF can be known as a specific type of observer and one of the best stochastic algorithm which can be used in estimation of rotor speed, flux, rotor or stator resistance and some other parameters. The stochastic method includes some errors in resolving the estimation parameters such as modelling errors, measurement errors of the system, random disturbances and computational inaccuracies. EKF is capable to filter and measure the noise of system by obtaining a minimum covariance error that will lead to optimal estimated states [9].

Generally, for estimation of load torque and rotor speed in IMs six state variables namely, stator currents, rotor fluxes, load torque and rotor speed are considered. In this paper, with reducing of state variables to five, the load torque and rotor speed is estimated. Actually, in this paper, the load torque plus rotor speed is considered as a state variable. Matlab simulation results will be presented to confirm the presented method. This paper is organized as follows: In part 2, d-q model of single-phase IM is presented. After that, a brief overview on conventional EKF for estimation of load and speed in single-phase IM is discussed in part 3. Besides, the

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proposed method for estimation of load and speed in single-phase IM is expounded in this section. The simulation results are shown in part 4 and part 5 concludes the paper.

2. The Single-phase IM Model

The dynamic model of single-phase induction machine in the stationary reference frame can be written as following equations [1]:

$$v_{ds}^s = r_{ds} i_{ds}^s + p\lambda_{ds}^s \tag{1}$$

$$v_{qs}^s = r_{qs} i_{qs}^s + p\lambda_{qs}^s \tag{2}$$

$$0 = r_r i_{dr}^s + p\lambda_{dr}^s + \omega_r \lambda_{qr}^s \tag{3}$$

$$0 = r_r i_{qr}^s + p\lambda_{qr}^s - \omega_r \lambda_{dr}^s \tag{4}$$

$$\lambda_{ds}^s = L_{ds} i_{ds}^s + M_d i_{dr}^s \tag{5}$$

$$\lambda_{qs}^s = L_{qs} i_{qs}^s + M_q i_{qr}^s \tag{6}$$

$$\lambda_{dr}^s = M_d i_{ds}^s + L_r i_{dr}^s \tag{7}$$

$$\lambda_{qr}^s = M_q i_{qs}^s + L_r i_{qr}^s \tag{8}$$

$$T_e = 1.5P(M_q i_{qs}^s i_{dr}^s - M_d i_{ds}^s i_{qr}^s) \tag{9}$$

$$P(T_e - T_l) = Jp\omega_r \tag{10}$$

Where, v^s_{ds}, v^s_{qs}, i^s_{ds}, i^s_{qs}, i^s_{dr}, i^s_{qr}, λ^s_{ds}, λ^s_{qs}, λ^s_{dr} and λ^s_{qr} are the d-q axes voltages, currents, and fluxes of the stator and rotor in the stationary reference frame (superscript “s”). r_{ds}, r_{qs} and r_r denote the stator and rotor resistances. L_{ds}, L_{qs}, L_r, M_d and M_q denote the stator, and the rotor self and mutual inductances. ω_r is the machine speed. p and P are differential operator and pole pairs. τ_e, τ_l and J are electromagnetic torque, load torque and inertia.

3. EKF Algorithm for Single-phase IM

The steady space model of single-phase machine can be expressed as follows:

$$\dot{x} = Ax + Bu + w(t) \tag{11}$$

$$y = Cx + v(t) \tag{12}$$

The covariance matrices of noises are also defined as (13) and (14):

$$Q = \mathrm{cov}(w) = E\{ww^t\} \tag{13}$$

$$R = \mathrm{cov}(v) = E\{vv^t\} \tag{14}$$

The Kalman filter algorithm can be formulated as (15)-(21) [26].
Prediction of State:

$$x_{n+1\ n} = \Phi\left(n+1, n, x_{n\ n-1}, u_n\right) \tag{15}$$

Where:

$$\Phi\left(n+1, n, x_{n\ n-1}, u_n\right) = A_n\left(x_{n\ n}\right)x_{n\ n} + B_n\left(x_{n\ n}\right)u_n \tag{16}$$

Estimation of Error Covariance Matrix:

$$P_{n+1\ n} = \frac{d\Phi}{dx}\Big|_{x=x_{n\ n}} P_{n\ n} \frac{d\Phi^T}{dx}\Big|_{x=x_{n\ n}} + Q \tag{17}$$

Computation of Kalman Filter Gain:

$$K_n = P_{n\ n-1}\frac{\partial H^T}{\partial x}\Big|_{x=x_{n\ n-1}}\left(\frac{\partial H}{\partial x}\Big|_{x=x_{n\ n-1}} P_{n\ n-1}\frac{\partial H^T}{\partial x}\Big|_{x=x_{n\ n-1}} + R\right)^{-1} \tag{18}$$

Where:

$$H\left(x_{n\ n-1}, n\right) = C_n\left(x_{n\ n-1}\right)x_{n\ n-1} \tag{19}$$

State Estimation:

$$x_{n\ n} = x_{n\ n-1} + K_n\left(y_n - H\left(x_{n\ n-1}, n\right)\right) \tag{20}$$

Update of the Error Covariance Matrix:

$$P_{n\ n} = P_{n\ n-1} - K_n\frac{\partial H}{\partial x}\Big|_{x=x_{n\ n-1}} P_{n\ n-1} \tag{21}$$

All of parameters in (11)-(21) are defined in Appendix. Based on (11)-(21), the EKF block diagram is shown in Figure 1.

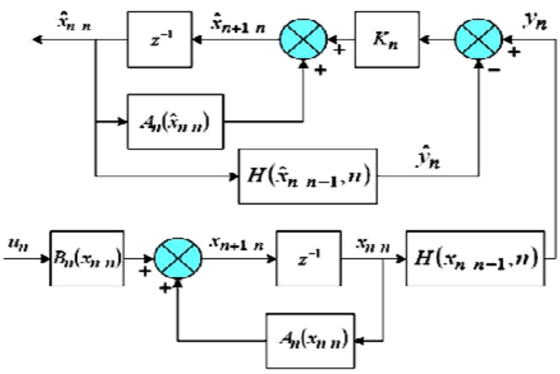

Figure 1. EKF block diagram

Normally, for estimation of load torque (T_l) and rotor speed (ω_r), the state, input and output matrices are defined as following equations [8]:

$$x_n = \begin{bmatrix} i_{ds}^{(n)} & i_{qs}^{(n)} & \lambda_{dr}^{(n)} & \lambda_{qr}^{(n)} & \omega_r^{(n)} & T_l^{(n)} \end{bmatrix}^T \quad (22)$$

$$y_n = \begin{bmatrix} i_{ds}^{(n)} & i_{qs}^{(n)} \end{bmatrix}^T \quad (23)$$

$$u = \begin{bmatrix} v_{ds}^{(n)} & v_{qs}^{(n)} \end{bmatrix}^T \quad (24)$$

The state space equations of single-phase IM and moreover the matrices A_n , B_n and C_n can be written as equation (25)-(31). With these equations and with considering of EKF algorithm the load torque and rotor speed can be estimated.

$$\begin{bmatrix} pi_{ds}^s \\ pi_{qs}^s \\ p\lambda_{dr}^s \\ p\lambda_{qr}^s \end{bmatrix} =$$
$$\begin{bmatrix} \left(\frac{r_r M_d}{L_r k_1} + \frac{L_r r_{ds}}{M_d k_1}\right) & 0 & \frac{-r_r}{L_r k_1} & -\omega_r k_1 \\ 0 & \left(-\frac{r_{qs}}{k_2} + \left(\frac{1}{k_2}\right)\left(\frac{-M_q}{L_r}\right)\left(\frac{r_r M_q}{L_r}\right)\right) & \frac{1}{k_2}\left(\frac{-M_q}{L_r}\right)\omega_r & \frac{1}{k_2}\left(\frac{-M_q}{L_r}\right)\left(\frac{-r_r}{L_r}\right) \\ \frac{r_r M_d}{L_r} & 0 & \frac{-r_r}{L_r} & -\omega_r \\ 0 & \frac{r_r M_q}{L_r} & \omega_r & \frac{-r_r}{L_r} \end{bmatrix} \begin{bmatrix} i_{ds}^s \\ i_{qs}^s \\ \lambda_{dr}^s \\ \lambda_{qr}^s \end{bmatrix}$$
$$+ \begin{bmatrix} \frac{-L_r}{M_d k_1} & 0 \\ 0 & \frac{1}{k_2} \\ \left(\frac{L_r}{M_d}\right) + \left(\frac{L_r}{M_d}\right)\left(-L_{ds} + \frac{-M_d^2}{L_r}\right)\left(\frac{-L_r}{M_d k_1}\right) & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_{ds}^s \\ v_{qs}^s \end{bmatrix} + w(t) \quad (25)$$

$$\begin{bmatrix} i_{ds}^s \\ i_{qs}^s \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{ds}^s & i_{qs}^s & \lambda_{dr}^s & \lambda_{qr}^s & \omega_r & T_l \end{bmatrix}^T + v(t) \quad (26)$$

Where,

$$k_1 = M_d - \frac{L_{ds} L_r}{M_d} \quad (27)$$

$$k_2 = L_{qs} - \frac{M_q^2}{L_r} \quad (28)$$

$$A_n = \begin{bmatrix} 1+\left(\frac{r_r M_d}{L_r k_1} + \frac{L_r r_{ds}}{M_d k_1}\right)dt & 0 & \left(\frac{-r_r}{L_r k_1}\right)dt & \left(-\omega_r^{(n)} k_1\right)dt & 0 & 0 \\ 0 & 1+\left(-\frac{r_{qs}}{k_2} + \left(\frac{1}{k_2}\right)\left(\frac{-M_q}{L_r}\right)\left(\frac{r_r M_q}{L_r}\right)\right)dt & \frac{1}{k_2}\left(\frac{-M_q}{L_r}\right)\omega_r^{(n)} dt & \frac{1}{k_2}\left(\frac{-M_q}{L_r}\right)\left(\frac{-r_r}{L_r}\right)dt & 0 & 0 \\ \left(\frac{r_r M_d}{L_r}\right)dt & 0 & 1+\left(\frac{-r_r}{L_r}\right)dt & \left(-\omega_r^{(n)}\right)dt & 0 & 0 \\ 0 & \left(\frac{r_r M_q}{L_r}\right)dt & \omega_r^{(n)} dt & 1+\left(\frac{-r_r}{L_r}\right)dt & 0 & 0 \\ \left(\frac{-M_d \lambda_{qr}^{(n)}}{J L_r}\right)\left(\frac{3}{2}\right)\left(\frac{P}{2}\right)^2 dt & \left(\frac{M_q \lambda_{dr}^{(n)}}{J L_r}\right)\left(\frac{3}{2}\right)\left(\frac{P}{2}\right)^2 dt & 0 & 0 & 1 & \left(\frac{-1}{J}\right)dt \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (29)$$

$$B_n = \begin{bmatrix} \frac{-L_r}{M_d k_1}dt & 0 & \left(\left(\frac{L_r}{M_d}\right)+\left(\frac{L_r}{M_d}\right)\left(-L_{ds}+\frac{-M_d^2}{L_r}\right)\left(\frac{-L_r}{M_d k_1}\right)\right)dt & 0 & 0 & 0 \\ 0 & \frac{1}{k_2}dt & 0 & 0 & 0 & 0 \end{bmatrix}^T \quad (30)$$

$$C_n = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (31)$$

One of the problems in the estimation of parameters using EKF is calculation of P and Q matrices. They are usually tuned by a trial and error process. In this paper, by considering of load torque plus rotor speed as one state variable, the order of P and Q matrices are decreased from six to five. The equations of single-phase motor can be written as equation (32) and (33).

$$\begin{bmatrix} pi_{ds}^s \\ pi_{qs}^s \\ p\lambda_{dr}^s \\ p\lambda_{qr}^s \end{bmatrix} = \begin{bmatrix} \left(\frac{r_r M_d}{L_r k_1}+\frac{L_r r_{ds}}{M_d k_1}\right) & 0 & \frac{-r_r}{L_r k_1} & \frac{-\omega_r}{k_1} \\ 0 & \left(-\frac{r_{qs}}{k_2}+\left(\frac{1}{k_2}\right)\left(\frac{-M_q}{L_r}\right)\left(\frac{r_r M_q}{L_r}\right)\right) & \frac{1}{k_2}\left(\frac{-M_q}{L_r}\right)\omega_r & \frac{1}{k_2}\left(\frac{-M_q}{L_r}\right)\left(\frac{-r_r}{L_r}\right) \\ \frac{r_r M_d}{L_r} & 0 & \frac{-r_r}{L_r} & -\omega_r \\ 0 & \frac{r_r M_q}{L_r} & \omega_r & \frac{-r_r}{L_r} \end{bmatrix} \begin{bmatrix} i_{ds}^s \\ i_{qs}^s \\ \lambda_{dr}^s \\ \lambda_{qr}^s \end{bmatrix}$$

$$+ \begin{bmatrix} \frac{-L_r}{M_d k_1} & 0 \\ 0 & \frac{1}{k_2} \\ \left(\frac{L_r}{M_d}\right)+\left(\frac{L_r}{M_d}\right)\left(-L_{ds}+\frac{-M_d^2}{L_r}\right)\left(\frac{-L_r}{M_d k_1}\right) & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_{ds}^s \\ v_{qs}^s \end{bmatrix} + w(t) + \begin{bmatrix} 0 & 0 & 0 & -T_l k_1 \\ 0 & 0 & \frac{1}{k_2}\left(\frac{-M_q}{L_r}\right)T_l & 0 \\ 0 & 0 & 0 & -T_l \\ 0 & 0 & T_l & 0 \end{bmatrix} \begin{bmatrix} i_{ds}^s \\ i_{qs}^s \\ \lambda_{dr}^s \\ \lambda_{qr}^s \end{bmatrix}$$

$$- \begin{bmatrix} 0 & 0 & 0 & -T_l k_1 \\ 0 & 0 & \frac{1}{k_2}\left(\frac{-M_q}{L_r}\right)T_l & 0 \\ 0 & 0 & 0 & -T_l \\ 0 & 0 & T_l & 0 \end{bmatrix} \begin{bmatrix} i_{ds}^s \\ i_{qs}^s \\ \lambda_{dr}^s \\ \lambda_{qr}^s \end{bmatrix} \quad (32)$$

$$= \begin{bmatrix} \left(\frac{r_r M_d}{L_r k_1}+\frac{L_r r_{ds}}{M_d k_1}\right) & 0 & \frac{-r_r}{L_r k_1} & -(\omega_r+T_l)k_1 \\ 0 & \left(-\frac{r_{qs}}{k_2}+\left(\frac{1}{k_2}\right)\left(\frac{-M_q}{L_r}\right)\left(\frac{r_r M_q}{L_r}\right)\right) & \frac{1}{k_2}\left(\frac{-M_q}{L_r}\right)(\omega_r+T_l) & \frac{1}{k_2}\left(\frac{-M_q}{L_r}\right)\left(\frac{-r_r}{L_r}\right) \\ \frac{r_r M_d}{L_r} & 0 & \frac{-r_r}{L_r} & -(\omega_r+T_l) \\ 0 & \frac{r_r M_q}{L_r} & (\omega_r+T_l) & \frac{-r_r}{L_r} \end{bmatrix} \begin{bmatrix} i_{ds}^s \\ i_{qs}^s \\ \lambda_{dr}^s \\ \lambda_{qr}^s \end{bmatrix}$$

$$+ \begin{bmatrix} \frac{-L_r}{M_d k_1} & 0 \\ 0 & \frac{1}{k_2} \\ \left(\frac{L_r}{M_d}\right)+\left(\frac{L_r}{M_d}\right)\left(-L_{ds}+\frac{-M_d^2}{L_r}\right)\left(\frac{-L_r}{M_d k_1}\right) & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_{ds}^s \\ v_{qs}^s \end{bmatrix} + w^*(t) \quad (33)$$

Therefore, the state, input and output matrices can be redefined as:

$$x_n = \left[i_{ds}^{(n)} \quad i_{qs}^{(n)} \quad \lambda_{dr}^{(n)} \quad \lambda_{qr}^{(n)} \quad \omega_r^{(n)} + T_l^{(n)} \right]^T \quad (34)$$

$$y_n = \begin{bmatrix} i_{ds}^{(n)} & i_{qs}^{(n)} \end{bmatrix}^T \tag{35}$$

$$u = \begin{bmatrix} v_{ds}^{(n)} & v_{qs}^{(n)} \end{bmatrix}^T \tag{36}$$

With these definitions, the order of state matrix is reduced form six to five. The matrices A_n , B_n and C_n are obtained as equation (37)-(39).

$$A_n = \begin{bmatrix} 1+\left(\frac{r_r M_d}{L_r k_1}+\frac{L_r r_{ds}}{M_d k_1}\right)dt & 0 & \left(\frac{-r_r}{L_r k_1}\right)dt & -k_1\left(\omega_r^{(n)}+T_l^{(n)}\right)dt & 0 \\ 0 & 1+\left(-\frac{r_{qs}}{k_2}+\left(\frac{1}{k_2}\right)\left(\frac{-M_q}{L_r}\right)\left(\frac{r_r M_q}{L_r}\right)\right)dt & \frac{1}{k_2}\left(\frac{-M_q}{L_r}\right)\left(\omega_r^{(n)}+T_l^{(n)}\right)dt & \frac{1}{k_2}\left(\frac{-M_q}{L_r}\right)\left(\frac{-r_r}{L_r}\right)dt & 0 \\ \left(\frac{r_r M_d}{L_r}\right)dt & 0 & 1+\left(\frac{-r_r}{L_r}\right)dt & -\left(\omega_r^{(n)}+T_l^{(n)}\right)dt & 0 \\ 0 & \left(\frac{r_r M_q}{L_r}\right)dt & \left(\omega_r^{(n)}+T_l^{(n)}\right)dt & 1+\left(\frac{-r_r}{L_r}\right)dt & 0 \\ \left(\frac{-M_d \lambda_{qr}^{(n)}}{JL_r}\right)\left(\frac{3}{2}\right)\left(\frac{P}{2}\right)^2 dt & \left(\frac{M_q \lambda_{dr}^{(n)}}{JL_r}\right)\left(\frac{3}{2}\right)\left(\frac{P}{2}\right)^2 dt & 0 & 0 & 1 \end{bmatrix} \tag{37}$$

$$B_n = \begin{bmatrix} \frac{-L_r}{M_d k_1}dt & 0 & \left(\left(\frac{L_r}{M_d}\right)+\left(\frac{L_r}{M_d}\right)\left(-L_{ds}+\frac{-M_d^2}{L_r}\right)\left(\frac{-L_r}{M_d k_1}\right)\right)dt & 0 & 0 \\ 0 & \frac{1}{k_2}dt & 0 & 0 & 0 \end{bmatrix}^T \tag{38}$$

$$C_n = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \tag{39}$$

4. Simulation Results

In this section, simulation results of the proposed method have been presented. The simulations have been done using Matlab/M-File software. The single-phase motor is fed by sinusoidal waveforms. The parameters of single-phase motor are listed as follows:

$$Power = 0.25hp, f = 60Hz, P = 4, J = 0.0146kg.m^2, v = 220V, r_r = 4.12\Omega, L_r = 0.1826H$$
$$r_{ds} = 7.14\Omega, r_{qs} = 2.02\Omega, L_{ds} = 0.1885H, L_{qs} = 0.1844H, M_d = 0.18H, M_q = 0.177H$$

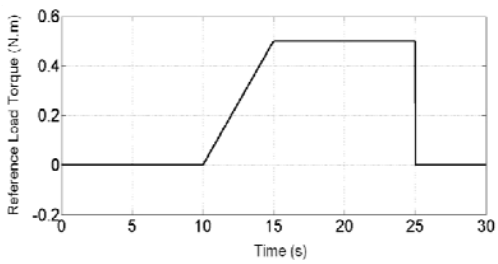

Figure 2. Reference load torque

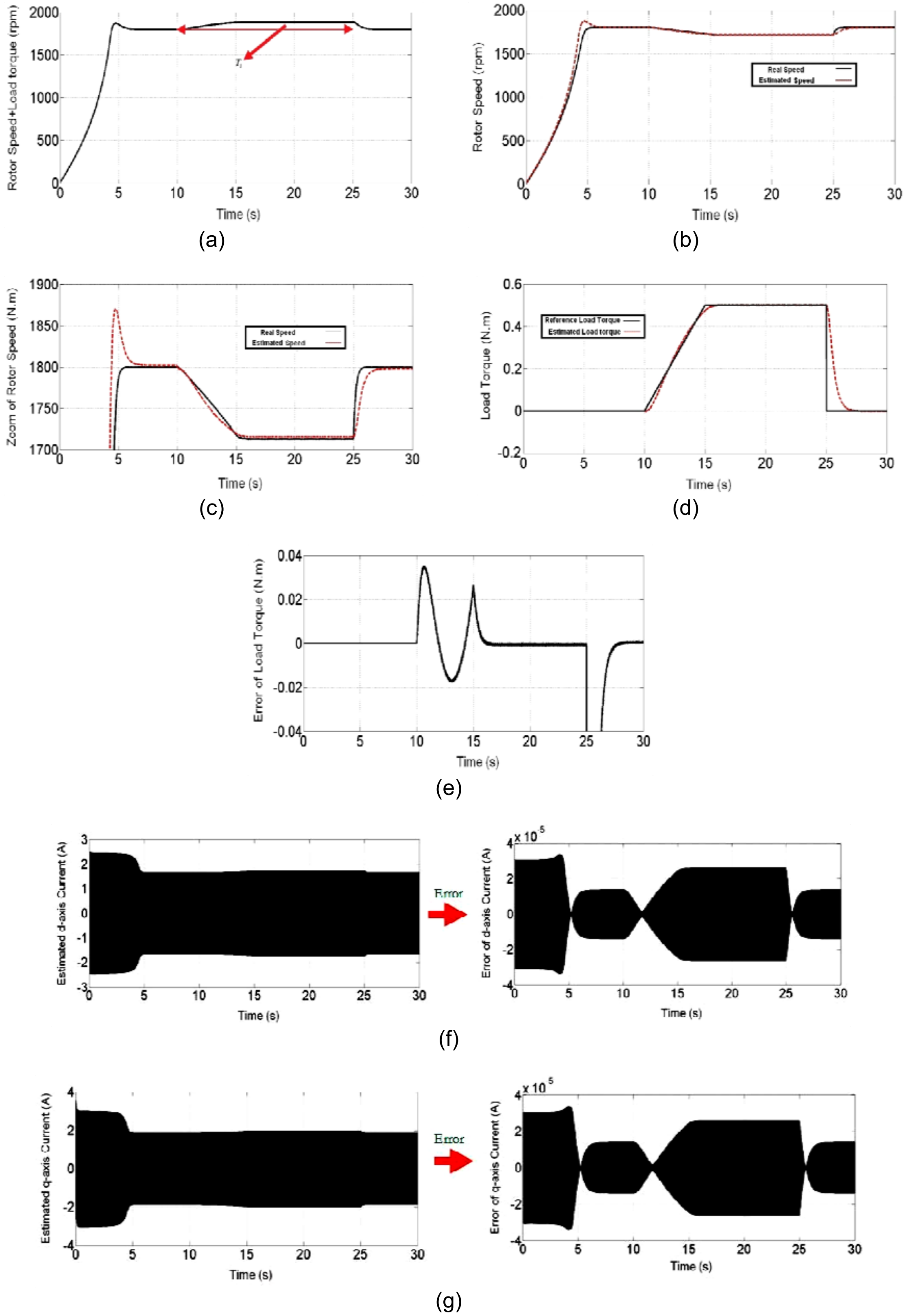

Figure 3. Simulation results of the estimation of load torque and rotor speed in single-phase IM using EKF

Figure 2 shows the reference load torque. In the simulations, the load torque is applied at t=10s and removed at t=25s. Figure 3 shows the simulation results of estimation of load torque and rotor speed in single-phase motor using presented EKF. As can be seen the real and estimated load torque and speed are very close (see Figure 3(b) and Figure 3(e)). As can be seen from Figure 3(c), the estimated speed follows the actual speed even when a load disturbance is introduced. It can be seen that the speed response rapidly with no pulsations. It is evident from Figure 3(f) and Figure 3(g) that the estimated values of stator d and q axes currents follow the actual values of stator d and q axes currents (the maximum error between estimated value of stator current and actual value of stator current is 3e-5).

5. Conclusion

In this paper, a method for estimation of load torque and rotor speed in single-phase IM using EKF has been presented. In this method, five parameters, namely, stator currents, rotor fluxes and load torque plus rotor speed has been considered. With these definitions the order of P and Q matrices in EKF algorithm is reduced form six to five. Results show the good performance of the proposed method.

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