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A Robust enlarged Kalman Filter for Speed-Sensorless Control of a Decoupled PMSM Drive and Linearized

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Abstract: *This paper utilizes a hearty input linearization system to guarantee a decent powerful execution, strength and a decoupling of the streams for Permanent Magnet Synchronous Motor (PMSM) in a turning reference outline (d, q). However this control requires the learning of certain factors (speed, torque, position) that are hard to access or its sensors require the extra mounting space, lessen the dependability in brutal conditions and increment the cost of engine. And furthermore a stator protection variety can incite an execution debasement of the framework. In this way a 6th request Discrete-time Extended Kalman Filter approach is proposed for on-line estimation of speed, rotor position, stack torque and stator protection in a PMSM. The intriguing reenactments comes about got on a PMSM subjected to the heap unsettling influence demonstrate extremely well the viability and great execution of the proposed nonlinear input control and Extended Kalman Filter calculation for the estimation within the sight of parameter variety and estimation commotion.*

Keywords: Robust Feedback Control, PMSM, Extended Kalman Filter, Estimation

1. Introduction

Lately, there has been a rising development of PMSM. This machine has been broadly utilized as a part of numerous in-dustrial applications. The principle points of interest, as contrasted and other AC engine drive, are high power factor, high control thickness, high torque to current proportion, high proficiency, Hence heartiness, bring down misfortune, bring down support what's more, less unpredictable engine can be gotten [1] [2]. In any case, the control of PMSM is demonstrated exceptionally troublesome on the grounds that the dynamic model of the PMSM is nonlinear, multidimensional and complex where a few parameters fluctuate with temperature or immersion. This nonlinear dynamic conduct prompts the utilization of nonlinear input control technique [3] [4] with a specific end goal to allow a decoupling of the PMSM factors in a (d, q) facilitate with the goal that stator streams can be independently controlled. Then again, to protect and enhance the dependability under parameters variety and clamors infused by the inverter (which can incite a state-space "coupling" and debasement of the framework), a powerful control approach has been made on the engine drives [5]-[7]. This control calculation utilizes H-interminability amalgamation of streams correctors with a specific end goal to guarantee vigorous dependability and exhibitions of the internal current circle. To ensure great exhibitions in nearness of parameters varieties (all the more particularly the stator protection furthermore, stack variety) and while progressed PMSM control procedures require information of the quick speed (which is hard to get to), the method in light of the state onlooker permitting an on-line estimation of the speed, position, stack torque and the stator protection is fundamental. Precise estimation of speed within the sight of estimation and framework clamor, and parameter varieties is a testing assignment. Kalman channel (KF) named after Rudolph E. Kalman [8] is a standout amongst the most surely understood and frequently utilized apparatuses for stochastic estimation. The KF is basically an arrangement of numerical conditions [9] [10] that execute an indicator corrector type estimator that is ideal as in it limits the assessed mistake covariance at the point when some assumed conditions are met. For the speed, torque and stator protection estimation issue of PMSM, where parameter variety and estimation clamor is available, KF is the perfect one. Numerous literary works on the KF method and its applications, basically stretched out for the estimation of the speed, have been distributed [11]-[13]. In any case, utilizing the nonlinear input control, this Extended KF (EKF) system doesn't consider the blend stack torque and stator protection variety. In the present research, after a short audit of the PMSM show, from one perspective a vigorous Input-yield linearization what's more, decoupling plan is produced and then again a 6th request discrete-time EKF, in view of KF rule, is proposed to evaluate the speed, streams, position and stretched out for the heap torque and stator protection reproduction. At long last, the proposed mix nonlinear input control and EKF approach are affirmed by reproductions comes about did on PMSM drive framework within the sight of estimation clamor and parameter varieties.

2. PMSM Equations and Robust Feedback Control

By expecting that the immersion of the attractive parts and the hysteresis marvel are disregarded; by considering the instance of a smooth-air-hole PMSM (where the inductances are equivalent: Ld = Lq) and as indicated by the field situated guideline where the immediate pivot current (Id) is constantly compelled to be zero which rearranges the elements what's more, accomplish most extreme electromagnetic torque per ampere, the PMSM display in the rotor reference (d, q) outline are as per the following [2] [5]:

$$\begin{cases} \dot{X} = F(X) + G \cdot U \\ Y = H(X) = \begin{bmatrix} h_1(X) & h_2(X) \end{bmatrix}^T = \begin{bmatrix} I_d & I_q \end{bmatrix}^T \end{cases} \quad (1)$$

with $X = \left[I_d I_q \Omega \theta \right]^T$, $U = \left[V_d V_q \right]^T$

$$F(X) = \begin{bmatrix} f_1(X) \\ f_2(X) \\ f_3(X) \\ f_4(X) \end{bmatrix} = \begin{bmatrix} -\frac{R_s}{L_d} I_d + \frac{L_q}{L_d} p \cdot I_q \cdot \Omega \\ -\frac{R_s}{L_q} I_q - \frac{L_d}{L_q} p \cdot I_d \cdot \Omega - \frac{p \cdot \Phi_f}{L_q} \Omega \\ -\frac{f}{J} \cdot \Omega + \frac{p \cdot \Phi_f}{J} I_q - \frac{T_L}{J} \\ p \cdot \Omega \end{bmatrix}; \quad G = \begin{bmatrix} \frac{1}{L_d} & 0 \\ 0 & \frac{1}{L_q} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} g_1 & 0 \\ 0 & g_2 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

This Equation (1) shows that the dynamic model of PMSM is nonlinear because of the coupling between the electrical currents and some parameters (in particular Rs) vary with temperature. Thus, in order to control independently the currents (Id, Iq) and then preserve the robustness performance and stability of the system under parameters variation and measurement noise, we can uses a robust feedback linearization strategy to regulate the motor states [18]. Thus, we can see that the system (1) has relative degree r1 = r2 = 1 and can be transformed into a linear and controllable system by chosen:

• a suitable and an appropriate change of coordinates given by:

$$z_1 = h_1(x); \quad z_2 = h_2(x) \text{ with} \quad (2)$$

where $[v_1, v_2]$ T are the new input vector of the obtained decoupled systems

• the feedback linearization control having the following form:

$$u = \begin{bmatrix} L_g h_1(x) & 0 \\ 0 & L_g h_2(x) \end{bmatrix}^{-1} \cdot \begin{bmatrix} v_1 - L_f h_1(x) \\ v_2 - L_f h_2(x) \end{bmatrix} = \begin{bmatrix} \frac{1}{L_q} & 0 \\ 0 & \frac{1}{L_d} \end{bmatrix}^{-1} \begin{bmatrix} v_1 - f_1 \\ v_2 - f_2 \end{bmatrix} \quad (3)$$

This feedback control (3) is effective and leads the system (1) to two decoupled subsystems;

• and two robust controllers C(s), using H∞ synthesis and "Doyle method" [6] [14], defined as:

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$$C(s)=\frac{J(s)\cdot H(s)^{-1}}{1-J(s)} \text{ with } J(s)=\frac{1}{(1+t_0 s)^2} \text{ and } H(s)=\frac{1}{1+Ts} \quad (4)$$

The real t0 is an adjusting positive parameter, chosen adequately small (t0 < 1), in order to satisfy the robustness performance, to have a good regulation and convergence of the currents. The block diagram structure for the control of (Id, Iq) can be summarized as follows in Figure 1. However the control of a PMSM generally required the knowledge of the instantaneous speed of the rotor that is not measurable. Also a variation of the stator resistance or/and load torque (Rs and TL) can induce a lack of field orientation. In order to achieve better dynamic performance, an on-line estimation of rotor speed, stator resistance and load torque is necessary. In this study, in order to respect to the parametric variations in the presence of measurement and system noise (stochastic estimation), an EKF's algorithm for speed estimation extended for the stator resistance and load torque reconstruction, is presented and explained in the next section.

3. Model of Extended Kalman Filter

For parameter estimation using a full order EKF, the model structure (1) is discretized directly using Euler approximation (1st order) proposed in [15]. Furthermore, the state vector is extended to the stator resistance and load torque. Thus, choosing the currents (Id, Iq), speed (Ω), rotor position (θ), load torque (TL) and stator resistance (Rs) as state variables, the voltages (Vd, Vq) as inputs, the new discrete-time and Stochastic sixth-order nonlinear dynamic model for the PMSM is described by Equation (5):

$$\begin{cases} X_e(k+1)=f\left(X_e(k),U(k)\right)+n(k)=X_e(k)+T_e\cdot Q\left(x_e(k),U(k)\right)+n(k) \\ Y_e(k)=h\left(X_e(k)\right)+r(k) \end{cases} \quad (5)$$

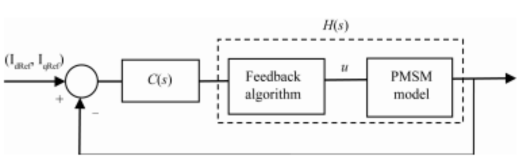

Figure 1. Proposed currents control scheme.

where $X_e(k)=\left[I_d(k)I_q(k)\Omega(k)q(k)T_L(k)R_s(k)\right]^T$, $U(k)=\left[V_d(k)V_q(k)\right]^T$

$$Q\left(X_e(k),U(k)\right)=\begin{bmatrix} -\frac{R_s(k)}{L_d}I_d(k)+\frac{L_q}{L_d}p\cdot I_q(k)\cdot\Omega(k)+\frac{1}{L_d}V_d \\ -\frac{R_s(k)}{L_q}I_q(k)-\frac{L_d}{L_q}p\cdot I_d(k)\cdot\Omega(k)-\frac{p\cdot\Phi_f}{L_q}\Omega(k)+\frac{1}{L_q}V_q \\ -\frac{f}{J}\cdot\Omega(k)+\frac{p\cdot\Phi_f}{J}I_q(k)-\frac{T_L(k)}{J} \\ p\cdot\Omega(k) \\ 0 \\ 0 \end{bmatrix}$$

$$Y_e(k)=\begin{pmatrix} I_d \\ I_q \end{pmatrix}=h\left(X_e(k)\right)=\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}\cdot X_e(k)=H\cdot X_e(k)$$

The resulting output vector Y_e (k) consists of the estimated motor current in a rotor reference frame being compared to the measured current. The difference is used to correct the state vector of the system model

The state vector and output, respectively at the k-th sampling instant, i.e. e t kT = · with Te the adequate sampling period chosen without failing the stability and the accuracy of the discrete-time model.

The random disturbance input, represented by, is the sum of modeling uncertainty, the discretization errors and the system noise. The measurement noise is represented by. Both n k( ) and r k( ) , are assumed to be white Gaussian noise with zero mean and covariance matrix Q and R respectively. Consider that:

- $\hat{X}_e(k)$ = the estimate of $X_e(k)$ and $K(k+1)$ = EKF gain;
- $\hat{X}_e(k+1|k)$ = the linear minimum mean square estimate of $X_e(k+1)$;
- $P(k+1|k)$ = state prediction covariance error;
- $P(k+1|k+1)$ = state estimation covariance error;
- Initialization givens: $\hat{X}_e(0|0)=\hat{X}_e(0)$ and $P(0|0)=P(0)$.

The steps of the proposed sixth-order Discrete-time Extended Kalman Filter algorithm are as follows:

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$$\begin{cases} 1)\ \hat{X}_e(k+1|k) = f\left(\hat{X}_e(k|k), U(k)\right) \\ 2)\ F(k) = \left.\dfrac{\partial f\left(\hat{X}(k), U(k)\right)}{\partial \hat{X}(k)}\right|_{X_e(k)=X_e(k|k)} \\ 3)\ P(k+1|k) = F(k)\cdot P(k|k)\cdot F^T(k) + Q \\ 4)\ K(k+1) = P(k+1|k)\cdot H^T\left[H\cdot P(k+1|k)\cdot H^T + R\right]^{-1} \\ 5)\ \Delta Y_e(k+1|k) = Y_e(k+1) - H\cdot \hat{X}_e(k+1|k) \\ 6)\ \hat{X}_e(k+1|k+1) = \hat{X}_e(k+1|k) + K(k+1)\cdot \Delta Y_e(k+1|k) \\ 7)\ P(k+1|k+1) = \left[I - K(k+1)\cdot H\right]\cdot P(k+1|k) \\ 8)\ \text{Increment } k \text{ and Go to step 1} \end{cases} \tag{6}$$

The EKF algorithm consists of repeated use of step (1-8) for each measurement is the Jacobian matrix of partial derivatives of f (•) with respect to. From Equation (5), we obtain:

$$F(k) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} + T_e \cdot \begin{bmatrix} -\dfrac{R_s(k)}{L_d} + p\cdot\Omega(k) + p\cdot I_q(k) - \dfrac{I_d(k)}{L_d} + \dfrac{1}{L_d}V_d \\ -\dfrac{R_s(k)}{L_q} - p\cdot\Omega(k) - p\cdot I_d(k) - \dfrac{p\cdot\Phi_f}{L_q} - \dfrac{I_q(k)}{L_q} + \dfrac{1}{L_q}V_q \\ -\dfrac{f}{J} + \dfrac{p\cdot\Phi_f}{J} - \dfrac{1}{J} \\ p \\ 0 \\ 0 \end{bmatrix} \tag{7}$$

4. Simulation Results and Discussion

The proposed robust nonlinear feedback control combined with a EKF strategy has been investigated with simulation tests carried out for a 1.6 kW PMSM by means of SIMULINK in order to illustrate its effectiveness against load, measurement noise and parameter variation (Figure 2). The nominal parameters of the PMSM, determined by means of the least-squares identification techniques proposed by the references [16] [17], are shown in the Table 1.

In order to evaluate its robustness and effectiveness, the comparisons between the estimated state variables and the simulated ones have been realized for several operating conditions with the presence of about 15% white noise on the measured currents and with additional load torque. Thus the simulations are obtained at first in the nominal case with the parameters of the PMSM (Table 1) and then in the second case, with 50% variation of the nominal stator resistance (Rs = 1.5 Rsn) in order to verify the behavior of the proposed EFK algorithm estimator with respect to stator resistance and load torque variation.

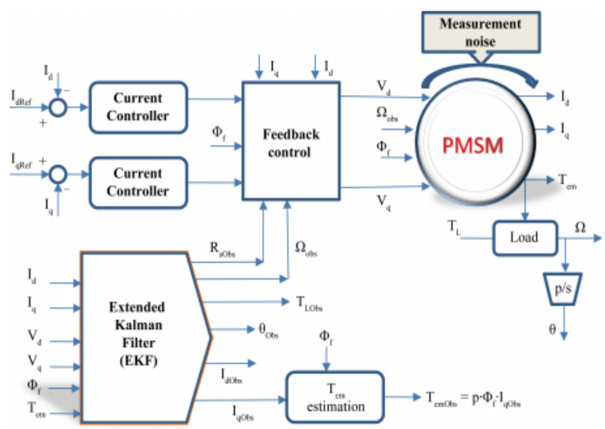

Figure 2. Simulation scheme.

Table 1. Nominal parameters of the PMSM.

$P_{mn} = 1.6$ kW	$U_n = 220/380$ V	$f_n = 0.0162$ N·m·sec·rad^{-1}
$p = 3$	$\Omega_n = 1000$ rpm	$J_n = 0.0049$ kg·m^2
$R_{sn} = 2.06\ \Omega$	$Phif_n = 0.29$ Wb	$L_{qn} = L_{dn} = 9.15$ mH

Initialization and Tuning of the EKF Algorithms

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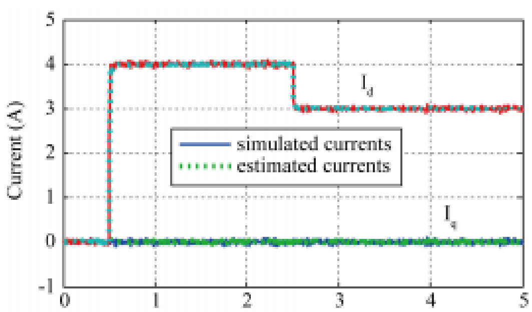
The important and difficult part in the design of the full order EKF is choosing the proper values for the covariance matrices Q and R. The change of values of covariance matrices affects both the dynamic and steady-state. In order to have a good performance, to insure better stability, convergence time and considerable rapidity of the EKF, the chosen values for the covariance matrices Q, R and P can be initialized and adjusted as follows:

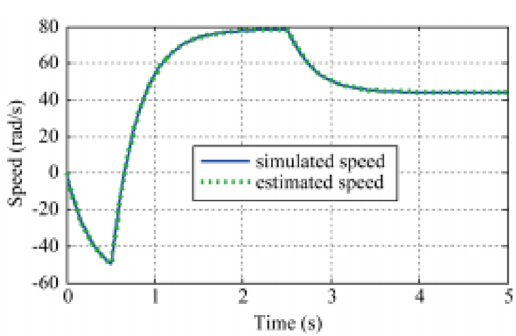
$$P_{6x6}(0) = diag\{10^4\}\ ;\ \ R_{2x2} = diag\{10^3\};\ \ Q_{6x6} = diag\{q\},$$

the real qi must be tuned adequately small:

Our proposed Feedback control and EKF algorithm operate with a sampling period Te = 1 ms and using Euler approximation. Experiment simulation were performed and examined with regards to the following tasks: possibility current changing and load torque acting. Figure 3 and Figure 4 show the responses of the currents, speed, rotor position, load torque and stator resistance for a step variation of the current reference (IdRef) under noisy conditions.

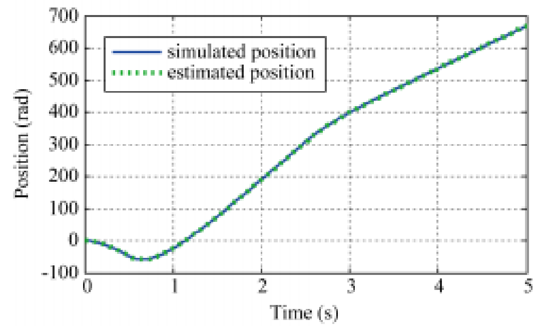


(a)



(b)

(a)



(c)

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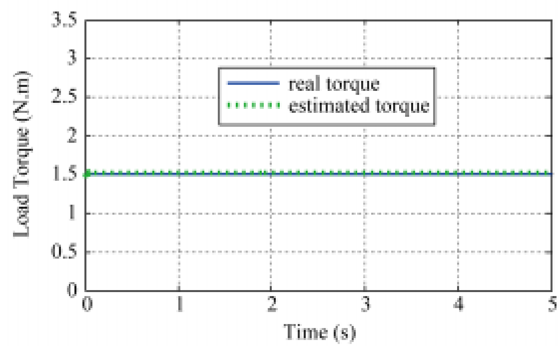
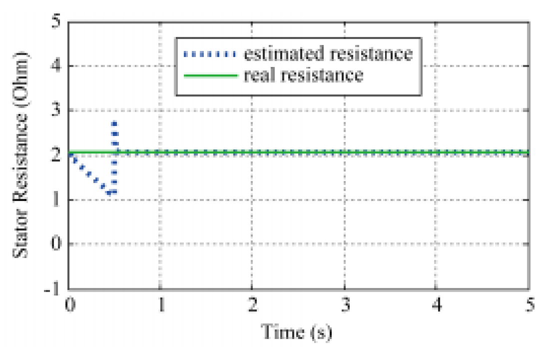


(d)



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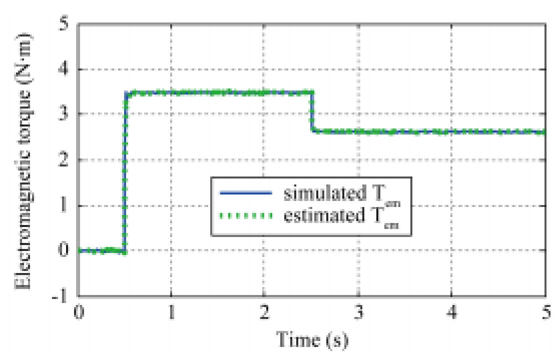

(f)

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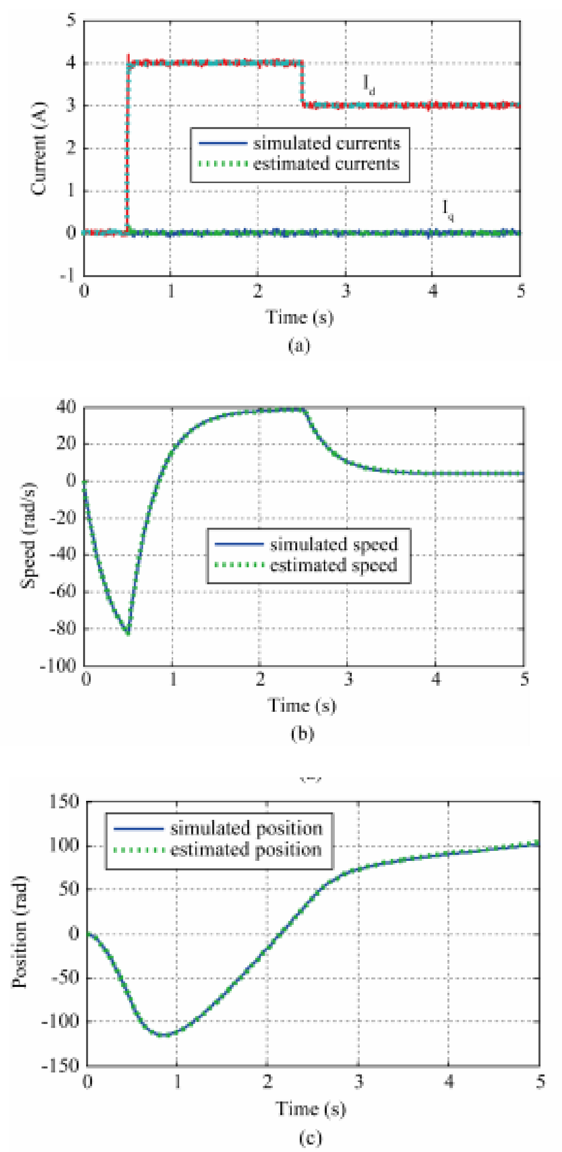
Figure 3. Nominal case (Rr = Rrn): Comparison between estimated and simulated values for TL = 1.5 N·m in the presence of measurement noises.



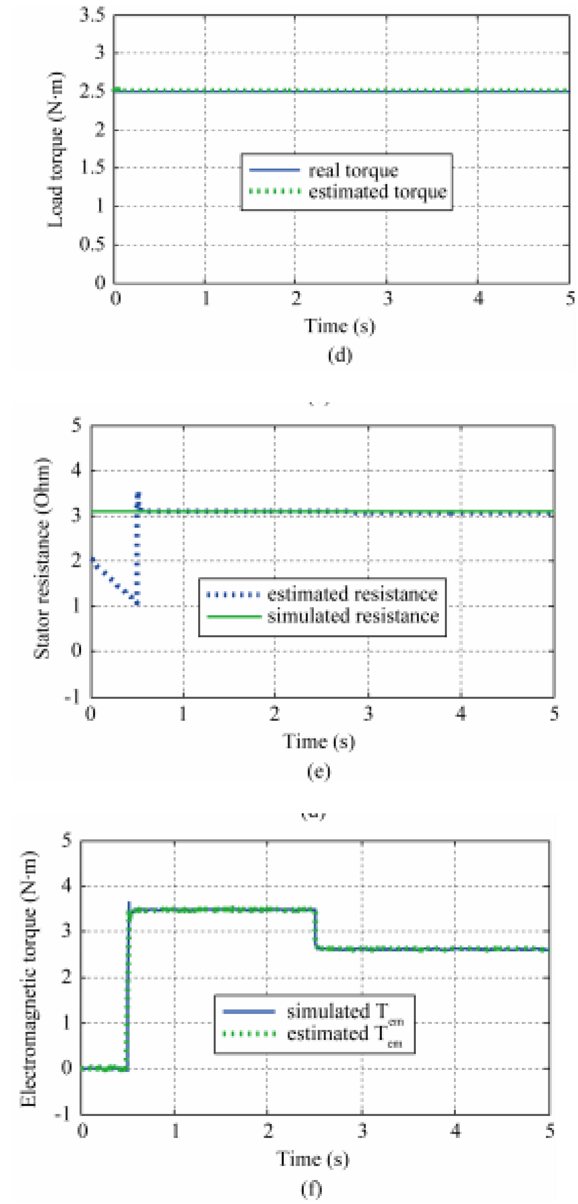


Figure 4. Non nominal case (Rr = 1.5*Rrn): Comparison between estimated and simulated values for TL = 2.5 N·m in the presence of measurement noises.

One can see that in both nominal (Figure 3) and non-nominal cases (Figure 4 where Rr = 1.5 Rrn), the estimated values of currents, speed, rotor position and load torque converge very well to their simulated values and are not affected too much from the injected noise. The observed better speed responses

(Figure 3(b), Figure 4(b)), in the presence of parameter uncertainty and measurement noises, indicate the good regulation and convergence of the currents (with a decoupled system) due to a favorable stator resistance (Figure 3(e), Figure 4(e)) and load torque estimation (Figure 3(d), Figure 4(d)). These good waveforms illustrate the fast convergence and high performance of the robust decoupling control and EKF algorithm against modeling uncertainty, parametric variation and measurement noise.

5. Conclusions

We have appeared in this work a powerful nonlinear criticism control joined with an EKF approach have been acknowledged to allow a linearization, decoupling and direction of the PMSM states (streams) keeping in mind the end goal to guarantee a great dynamic execution of the worldwide framework and for taking care of scope of issues in sensorless (speed, rotorposition and load torque) control of PMSM drive without mechanical sensor. The intriguing reproduction comes about acquired on the PMSM demonstrate the viability, the joining and the dependability of the proposed control in nearness of stator protection variety, estimated clamor and load. Along these lines in the modern applications, due to the monetary focal points (particularly for low-controlled engines), one will acknowledge extremely well the trial actualize of this powerful EKF sensorless control calculation to substitute the PMSM mechanical sensor for the reconstitution of the speed, rotor position, stack torque and stator protection.

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