International Journal of Electrical and Computer Engineering (IJECE)
Vol. 13, No. 1, February 2023, pp. 17~27
ISSN: 2088-8708, DOI: 10.11591/ijece.v13i1.pp17-27

Optimized Kalman filters for sensorless vector control induction motor drives

Mohammed Khalil Hussain[1], Bajel Mohammed Alshadeedi[2], Rashid Hejeejo[3]
[1]Department of Energy Engineering, University of Baghdad, Baghdad, Iraq
[2]Department of Reconstruction and Projects, University of Baghdad, Baghdad, Iraq
[3]Ministry of Higher Education and Scientific Research, Department of Construction and Projects, Baghdad, Iraq

Article Info

Article history:

Received Apr 18, 2022
Revised Jul 15, 2022
Accepted Aug 2, 2022

Keywords:

Extended Kalman filter
Induction motor
Multi objective optimization
Sensorless vector control
Unscented Kalman filter

ABSTRACT

This paper presents the comparison between optimized unscented Kalman filter (UKF) and optimized extended Kalman filter (EKF) for sensorless direct field orientation control induction motor (DFOCIM) drive. The high performance of UKF and EKF depends on the accurate selection of state and noise covariance matrices. For this goal, multi objective function genetic algorithm is used to find the optimal values of state and noise covariance matrices. The main objectives of genetic algorithm to be minimized are the mean square errors (MSE) between actual and estimation of speed, current, and flux. Simulation results show the optimal state and noise covariance matrices can improve the estimation of speed, current, torque, and flux in sensorless DFOCIM drive. Furthermore, optimized UKF present higher performance of state estimation than optimized EKF under different motor operating conditions.

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Corresponding Author:

Mohammed Khalil Hussain
Department of Energy Engineering, Faculty of Engineering, University of Baghdad
Karrada, Al-Jadriya, Baghdad, Iraq
Email: mohammedkhalil@uobaghdad.edu.iq

1. INTRODUCTION

Field orientation control induction motor (FOCIM) drives are widely used in high performance industrial applications when high torque and speed response are required [1], [2]. Furthermore, the main advantage of FOCIM drives is decupling control between torque and flux as separately excited direct current (DC) motor [2], [3]. In order to archive the high performance in direct field orientation control induction motor (DFOCIM) drive, accurate measurements of rotor speed and flux are required [4]. These measurements are provided by Hall sensors and sensing coils for flux measurement as well as the incremental encoder for rotor speed measurement. However, these sensors imply high cost, size, and weight as well as, lower reliability and difficult of installing [2], [5], [6]. In recent years, elimination of these sensors has been considered and the speed and flux are estimated based on voltage and current terminals to represent the senserless vector control drives [6].

In the last decade, Kalman filter algorithms have been used for the estimation of the rotor speed and flux in induction motor drives [7]. Extended Kalman filter (EKF) and unscented Kalman filter (UKF) are used to estimate the rotor speed of induction motor [2], [6]–[8]. UKF is used to estimate the speed and current FOCIM drives [9]–[12]. EKF is used to estimate the rotating speed in FOCIM drives [6], [8], [13], [14]. On the other hand, the main point in EKF and UKF is covariance matrix (Q) and measurement noise matrix (R) which are unknown matrices. These matrices were tuned manually based on trial and error method [6]–[15]. The performance of EKF and UKF highly depends on the right selection for the covariance matrices [15]. Recently, optimization algorithms are used to tunned the covariance and measurement noise matrices based on minimizing the mean squared error (MSE) between the actual and estimation of measuring response. Single objective optimization algorithms are used to estimate the covariance and measurement noise matrices based on specific minimization of MSE. Therefore, single objective practical swarm optimization (PSO) is used to optimize EKF for speed estimation based on minimizing MSE of the rotating speed [3], [7], [16], [17]. Also, single objective genetic algorithms are used to find the optimal tunning of the covariance and measurement noise matrices for the EKF based on minimizing MSE of the rotating speed [6], [18]. However, single objective optimization algorithms can reduce only the MSE for speed estimation and neglect the error on the other state estimation by means of flux, current, and torque. Therefore, multi objective function optimization algorithms are used to find optimal tunning of the covariance and measurement noise matrices based on minimizing the MSE in different state estimations of induction motor (IM). Multi objective genetic algorithm can reduce MSE of rotating speed and torque but MSE of current is increased [19], even though, the multi objective function of differential evolution algorithm is applied in EKF to find the optimal covariance and measurement noise matrices based on minizine the MSE of speed and current, the MSE of flux is not considered [20].

The main contribution of the present paper is to implement the multi objective genetic algorithm of the UKF and EKF to find the optimal values of state and noise covariance matrices. The optimal values of these matrices are optimized based on minimizing MSE between the actual and estimation of speed, current, and flux. Dynamic model of IM is presented and DFOCIM strategy has been included to improve torque/current capability via decoupling of stator current components. For enhancement of speed-controlled alternating current (AC) drive and increase its reliability, an accurate estimation of speed, current, and flux based on optimized UKF and optimized EKF have been included and compared. The proposed method is focused on finding the accurate state estimation for senserless DFOCIM drive. It is shown in both no-load and load conditions results that optimized UKF can find an accurate estimation of speed, current, and flux better than optimized EKF.

2. DYNAMIC MODEL OF INDUCTION MOTOR

The mathematical model of IM has four variables in the stationary reference frame (α, β); stator current ($I_{s\alpha}, I_{s\beta}$) and flux ($\Phi_{r\alpha}, \Phi_{r\beta}$). The induction motor model has been extended (e) to include the rotor speed (Ω).

$$\begin{cases} \dot{X}^e = AX^e + BU^e \\ Y^e = CX^e \end{cases} \tag{1}$$

$$\begin{cases} X^e = \left[I_{s\alpha}\ I_{s\beta}\ \Phi_{r\alpha}\ \Phi_{r\beta}\ \Omega\right]^T \\ U^e = \left[V_{s\alpha}\ V_{s\beta}\right]^T \\ Y^e = \left[I_{s\alpha}\ I_{s\beta}\right]^T \end{cases} \tag{2}$$

$$A = \begin{bmatrix} -\frac{1}{\tau'_\sigma} & 0 & \frac{K_r}{\tau'_\sigma R_\sigma \tau_r} & \frac{K_r}{\tau'_\sigma R_\sigma}\mathrm{P}\Omega & 0 \\ 0 & -\frac{1}{\tau'_\sigma} & -\frac{K_r}{\tau'_\sigma R_\sigma}\mathrm{P}\Omega & \frac{K_r}{\tau'_\sigma R_\sigma \tau_r} & 0 \\ \frac{M}{\tau_r} & 0 & -\frac{1}{\tau_r} & -P\Omega & 0 \\ 0 & \frac{M}{\tau_r} & P\Omega & -\frac{1}{\tau_r} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{3}$$

$$B = \begin{bmatrix} \frac{1}{\tau'_\sigma R_\sigma} & 0 \\ 0 & \frac{1}{\tau'_\sigma R_\sigma} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix},\ C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{4}$$

$$\tau'_\sigma = \sigma\frac{L_s}{R_\sigma}\ ;\ R_\sigma = R_s + K_r^2.R_r;\quad K_r = \frac{M}{L_r};\ \sigma = 1 - \frac{M^2}{L_s L_r};\quad \tau_r = \frac{L_r}{R_r} \tag{5}$$

Where A is state matrix, B is input matrix, C is output matrix, $V_{s\alpha}$ and $V_{s\beta}$ are the voltage in (α, β) frame. R_s, R_r are stator and rotor resistance; L_s, L_r, M are stator, rotor, and mutual inductance; P is Paris of pole [10], [11]. The (7) should be discretized by using Taylor series of order two to be applied to the digital implementation.

$$\begin{cases} X_{k+1} = A_k X_k + B_k U_k \\ Y_k = C_k X_k \end{cases} \tag{6}$$

3. KALMAN FILTER ALGORITHMS

In this paper, the EKF and UKF algorithms are used to find the estimation of current, flux, and rotor speed to be used in sensorless DFOCIM drive. However, the accurate estimation of these state variables by using Kalman filters depends on finding the optimal values of state and noise covariance matrices. The details of the EKF and UKF algorithms can be found in the following subsections.

3.1. Extended Kalman filter

To use a nonlinear model of IM with the extended EKF, the model must be linearized about the current operating point (k), giving a linear perturbation model represented by a Jacobian matrix [6], [8], [14]:

$$\begin{cases} X_{k+1}^e = F_k(X_k^e, U_k^e) + W_k = A_k^e X_k^e + B_k^e U_k^e + W_k \\ Y_k^e = H_k(X_k^e) + V_k = C_k^e X_k^e + V_k \end{cases} \tag{7}$$

$$A_k^e = \frac{dF_k}{dX^e}\bigg|_{X_k^e = \hat{X}_k^e}; \quad B_k^e = \frac{dF_k}{dU_k^e}\bigg|_{X_k^e = \hat{X}_k^e}; \quad C_k^e = \frac{dH_k}{dX^e}\bigg|_{X_k^e = \hat{X}_k^e} \tag{8}$$

where W_k, V_k are noise matrix of state and output model; d is derivative of the Jacobian matrix. The equations of EKF applied in IM drive used the model in (7) can be expressed:

$$\hat{X}^e{}_{\frac{k+1}{k}} = A^e{}_{k,k} \hat{X}^e_{\frac{k}{k}} + B^e_{\frac{k}{k}} U^e_k \tag{9}$$

$$P^e{}_{\frac{k+1}{k}} = A^e{}_{k,k} P^e{}_{\frac{k}{k}} A^e_{k,k}{}^T + Q^e_k \tag{10}$$

$$K^e{}_{k+1} = P^e{}_{\frac{k+1}{k}} C^e{}_k^T \left(C^e{}_k P^e{}_{\frac{k+1}{k}} C^{eT} + R_k \right)^{-1} \tag{11}$$

$$\hat{X}^e{}_{\frac{k+1}{k+1}} = \hat{X}^e{}_{\frac{k+1}{k}} + K^e{}_{k+1} \left(Y_{k+1} - C^e{}_k \hat{X}^e{}_{\frac{k+1}{k}} \right) \tag{12}$$

$$P^e{}_{\frac{k+1}{k+1}} = (I_5 - K^e{}_{k+1} C^e{}_k) P^e{}_{\frac{k+1}{k}} \tag{13}$$

where P^e is error covariance matrix; Q_k^e is covariance matrix of system noise; R_k is covariance matrix of measurement noise; and K^e is Kalman filter gain. Although the EKF is straightforward, it has instability solution due to the linearization and costly calculation due to Jacobian matrices.

3.2. Unscented Kalman filter

The UKF is used with nonlinear vectors of IM without needing any derivative and Jacobian approximations. In this paper nonlinear discrete time state transition equation [9]–[12].

$$\begin{cases} X_{k+1}^e = F_k(X_k^e, U_k^e) + W_k = A_k^e X_k^e + B_k^e U_k^e + W_k \\ Y_k^e = H_k(X_k^e) + V_k = C_k^e X_k^e + V_k \end{cases} \tag{14}$$

The UKF process is used to find the minimum mean square error (MMSE) then find the best state estimation of IM drive.

$$\hat{X}_k^e = E(X_k^e / Z_k) \tag{15}$$

Where $Z_k = (z_{1,} z_{2,} z_{3,} \ldots, z_n)$, and $E(X/Z)$ is the estimated value of X given the information Z. The covariance matrix $P^e{}_{\frac{k}{k}}$ is calculated based on the error estimation.

$$P^e{}_{\frac{k}{k}} = \left\{ \left[X_k^e - \hat{X}_{\frac{k}{k}}^e \right] \left[X_k^e - \hat{X}_{\frac{k}{k}}^e \right]^T / Z_k \right\} \tag{16}$$

The update equations of state estimation and covariance matrix are given as (17), (18):

$$\hat{X}_{\frac{k+1}{k+1}}^e = \hat{X}_{\frac{k+1}{k}}^e + K^e{}_{k+1} v_{k+1} \tag{17}$$

$$P^e{}_{\frac{k+1}{k+1}} = P^e{}_{\frac{k+1}{k}} - K^e{}_{k+1} P^{e\,v}{}_{\frac{k+1}{k}} K^{e\,T}{}_{k+1} \tag{18}$$

where v_{k+1} is innovation matrix, $P^{e\,v}{}_{\frac{k+1}{k}}$ is state innovation covariance matrix. The sigma points are selected to approximate n-dimensional of state variable X_k^e with $\hat{X}_{\frac{k}{k}}^e$ and $P^e{}_{\frac{k}{k}}$ into 2n+1 weighted sample. Finally, the estimation process of set of samples can be explained in three steps: i) first is transform each sigma point ($\chi_i^e{}_{\frac{k+1}{k}}$), ii) second is compute the state estimation ($\hat{\chi}^e{}_{\frac{k+1}{k}}$), and iii) third is calculate the estimation covariance matrix ($P^e{}_{\frac{k+1}{k}}$).

$$\chi_i^e{}_{\frac{k+1}{k}} = F_k \left(\chi_i^e{}_{\frac{k}{k}}, U_k^e \right) \tag{19}$$

$$\hat{\chi}^e{}_{\frac{k+1}{k}} = \sum_{i=0}^{2n} W_i \, \chi_i^e{}_{\frac{k+1}{k}} \tag{20}$$

$$P^e{}_{\frac{k+1}{k}} = \sum_{i=0}^{2n} W_i \left[\chi_i^e{}_{\frac{k+1}{k}} - \hat{\chi}^e{}_{\frac{k+1}{k}} \right] \left[\chi_i^e{}_{\frac{k+1}{k}} - \hat{\chi}^e{}_{\frac{k+1}{k}} \right]^T \tag{21}$$

4. DESIGN OPTIMIZATION OF EKF AND UKF ALGORITHMS

According to the theory of Kalman filter algorithms, Q, P, and R are unknown matrices and these matrices have to be obtained based on stochastic properties of the noises [7], [13], [14]. Therefore, in most cases using tunning experimental trial-and-error to achieve the best state estimation. Finding the correct parameters of those covariance matrices can reflect on the accurate state estimation based on Kalman filter algorithms. In this paper, the objective functions to be minimized are the MSE of speed, current, and flux to find an accurate estimation for all state estimation in senserless DFOCIM drive. The four main components in the design optimization of Kalman filters are defined:

4.1. Design variables

The design variables are components of Q, P, and R matrices:

$$Q = diag\,[Q_1 \quad Q_2 \quad Q_3 \quad Q_4 \quad Q_5] \tag{22}$$

$$P = diag\,[P_1 \quad P_2 \quad P_3 \quad P_4 \quad P_5] \tag{23}$$

$$R = diag\,[R_1 \quad R_2] \tag{24}$$

4.2. Objective function

The three main objectives to be minimized are MSE of speed (E_Ω), MSE of current (E_I), and MSE of flux E_Φ.

$$E_\Omega = \frac{1}{N} \sum_{n=1}^{N} (\Omega - \hat{\Omega})^2 \tag{25}$$

$$E_I = \frac{1}{N} \sum_{n=1}^{N} (I_{s\alpha} - \hat{I}_{s\alpha})^2 + (I_{s\beta} - \hat{I}_{s\beta})^2 \tag{26}$$

$$E_{\Phi} = \frac{1}{N}\sum_{n=1}^{N}(\Phi_{r\alpha} - \widehat{\Phi}_{r\alpha})^2 + (\Phi_{r\beta} - \widehat{\Phi}_{r\beta})^2 \quad (27)$$

4.3. Constraints

The constraints of the design variables are based on the minimum and maximum levels of each component in design variable.

$$\begin{gathered}\underline{Q_{1,2,3,4,5\,min}} \le Q_{1,2,3,4,5} \le \overline{Q_{1,2,3,4,5\,max}} \\ \underline{P_{1,2,3,4,5\,min}} \le P_{1,2,3,4,5} \le \overline{P_{1,2,3,4,5\,max}} \\ \underline{R_{1,2_{min}}} \le R_{1,2} \le \overline{R_{1,2_{max}}}\end{gathered} \quad (28)$$

Where $Q_{1,2,3,4,5\ \mathrm{min}}$ and $Q_{1,2,3,4,5\ \mathrm{max}}$ are the minimum and maximum diagonal covariance matrix values of noise system respectively. $P_{1,2,3,4,5\ \mathrm{min}}$and $P_{1,2,3,4,5\ \mathrm{max}}$ are the minimum and maximum diagonal Error covariance matrix values respectively. $R_{1,2_{min}}$ and $R_{1,2_{max}}$ are the minimum and maximum diagonal covariance matrix of measurement noise values respectively.

4.4. Optimization algorithm

The multi objective function optimization algorithm is used to find the optimal design variables based on maximizing or minimizing vector of the objective functions. In this paper, the genetic algorithm is used to find state and noise covariance matrices based on minimizing MSE of rotor speed, current, and flux. Genetic algorithms are designed based on the biological process. Therefore, much of the processes are based on genetics and natural selection. The genetic algorithm has seven processes to find the optimal solution. These processes are a selection of the parameters, encoding and decoding, population, natural selection, pairing, mating, and mutations. The genetic algorithm is iterated until the chromosome gives the same value of cost. This means the genetic algorithm has been converged. Detailed information about Genetic algorithms can be found in [21], [22].

5. OPTIMIZATION PROCEDURE

This section describes the procedure to find the optimal state and noise covariance matrices for UKF and EKF of sensorless DFOCIM drive. The steps are:

- Step 1: specify the initial value of the design variables (Q, P, and R matrices) for UKF and EKF according to (22)-(24).
- Step 2: calculate the estimation of speed ($\hat{\Omega}$), current ($\hat{I}_{s\alpha}$, $\hat{I}_{s\beta}$), and flux ($\widehat{\Phi}_{r\alpha}$, $\widehat{\Phi}_{r\beta}$) using UKF and EKF.
- Step 3: calculate the MSE of speed (E_{Ω}), MSE of current (E_I), and MSE of flux E_{Φ} according to (25)-(27).
- Step 4: specify each component of Q, P, and R matrices based on the minimum and maximum levels of matrices.
- Step 5: apply the multi objective function genetic algorithm based on minimizing MSE of speed, current, and flux.
- Step 6: update the values of the design variables (Q, P, and R matrices) for optimized UKF and optimized EKF based on optimization results.
- Step 7: the steps (2-6) are repeated until finding the optimal Q, P, and R matrices.

6. SENSORLESS DFOCIM DRIVE UNDERSTUDY

The EKF and UKF are used to estimate rotor speed and flux based on voltage and current probes of sensorless DFOCIM drive as shown in Figure 1. DFOC can achieve the decoupling between torque and flux [11], [14]. Park transforms used to change from (d, q) to (α, β) reference frame.

Space vector control (SVC) pulse width modulation is used as a control for three phase IM [23]–[25]. Table 1 shows the parameter of IM under test. Table 2 shows the minimum and maximum levels of Q, P, and R matrices. Table 3 shows the optimal components of Q, P, and R matrices by using the multi objective function genetic algorithm based on minimizing MSE of speed error (E_{Ω}) current error (E_I), and flux (E_{Φ}). In order to show the effectiveness of optimized EKF and optimized UKF in sensorless DFOCIM drive, two different operations conditions in IM have been used.

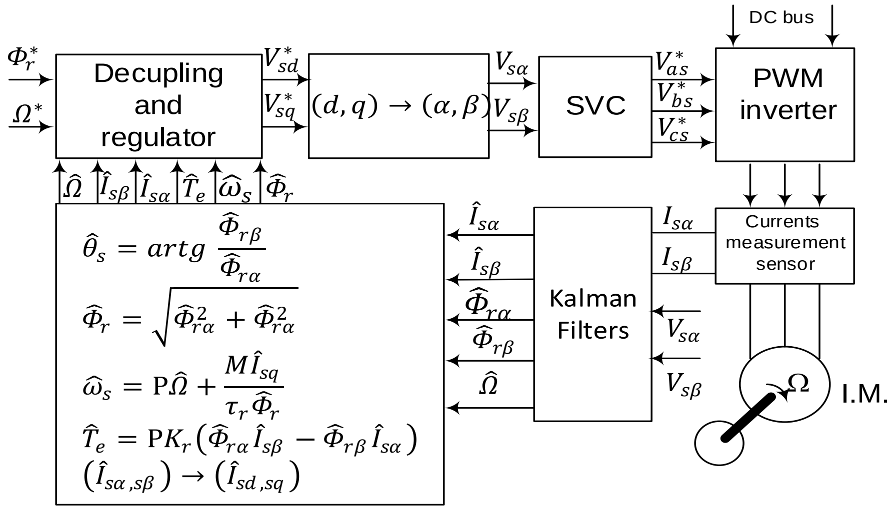


Figure 1. The complete system of sensorless DFOCIM drive with Kalman filter algorithms

Table 1. The parameter of IM

Variable	Unit	Value
Power P_n	[Kw]	7.5
Speed Ω_n	[Tr/min]	1450
Torque T	[Nm]	50
Paris of pole P	[p.u.]	2
Stator resistance R_s	[Ω]	0.63
Rotor resistance R_r	[Ω]	0.4
Stator inductance L_s	[H]	0.097
Rotor inductance L_r	[H]	0.091
Mutual inductance M	[H]	0.091
Moment of inertia J	[Kg.m^2]	0.22
Frequency f	[Hz]	50

Table 2. The constraints of Q, P, and R matrices

Matrix elements	Minimum	Maximum
Q_{1-5}	1e-20	1e20
P_{1-5}	1e-20	1e20
R_{1-2}	1e-20	1e20

Table 3. The optimal values of Q, P, and R matrices

Matrix elements	EKF	UKF
Q_1	1000	485.262
Q_2	9.998e-11	315.275
Q_3	1000	0.01361
Q_4	1000	0.0384
Q_5	1000	371.3083
P_1	14662533.238	0.0771
P_2	9423954.795	0.0412
P_3	11999.229	9.466e-05
P_4	4980.825	0.000101
P_5	41167535894.457	110.5567
R_1	9.99e-06	0.70058
R_2	1.5444	1.73586

6.1. No-load conditions

In this condition, there is no load applied to IM and the speed reference is tracking response (1,000 Turn/min. from the beginning until 1.5 sec. and -1000 Turn/Min from 1.5 sec. until 3 sec.). As shown in Figures 2(a) and 2(b) (in appendix), optimized EKF and optimized UKF can estimate the speed, flux, current, and torque in sensorless DFOCIM drive. Also, the error between actual and estimation response in optimized UKF is less than optimized EKF in most estimation parameters.

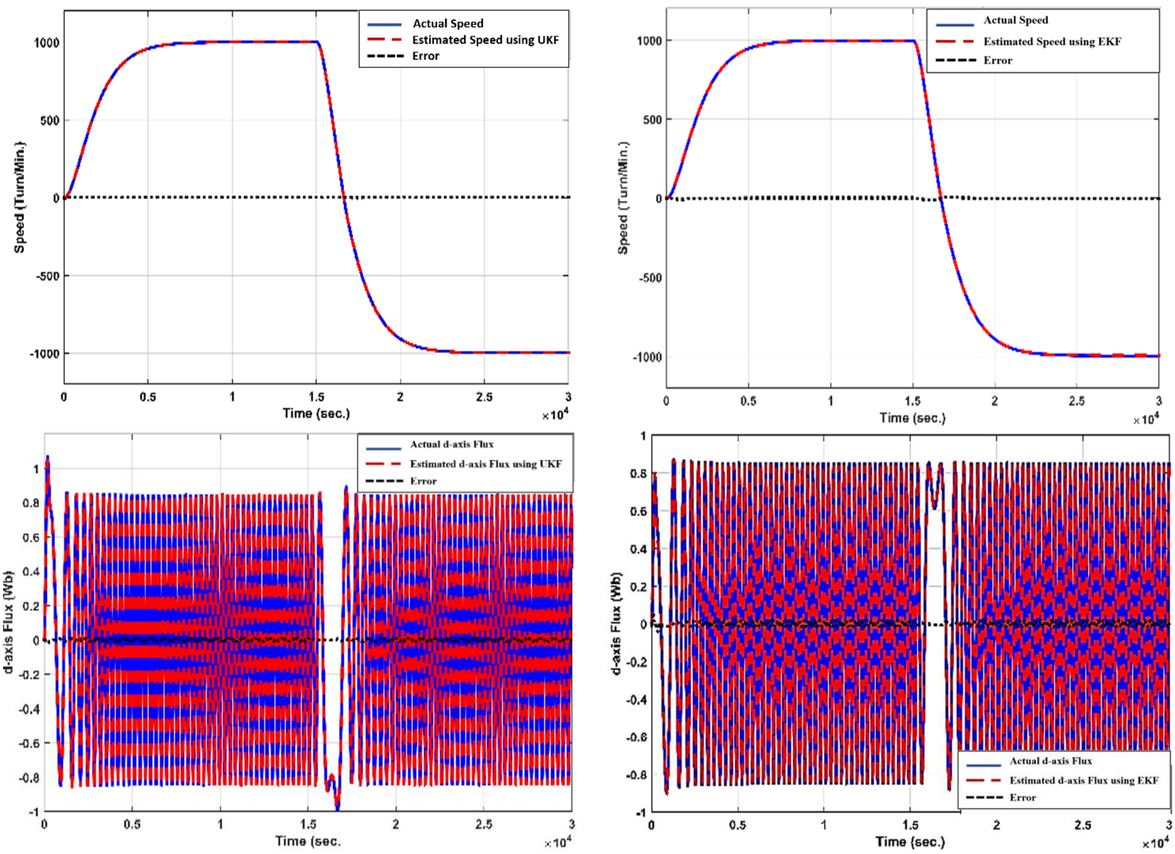
6.2. Load conditions

In this section check the robustness of the system in different rotations of speed and sudden load. 50 Nm load has been applied in 0.8 sec when the speed reference is tracking response. As shown in Figures 3(a) and 3(b) (in appendix), UKF and EKF can track speed, current, flux, and torque after adding the load at a specific time. The convergence speed of the genetic algorithm takes about (344.706 min.) for optimized EKF and (232.374 min.) for optimized UKF in a powerful computer server with two Intel Xeon processors (CPU X5650) operating at 2.67 GHz (2 processors) and 64 GB of RAM. Table 4 (in appendix) shows the comparison in MSE between optimized UKF and EKF in no-load and load conditions. As shown in this table, MSE of speed, current, flux, and torque by using optimized UKF are less than optimized EKF in different operation conditions.

7. CONCLUSION

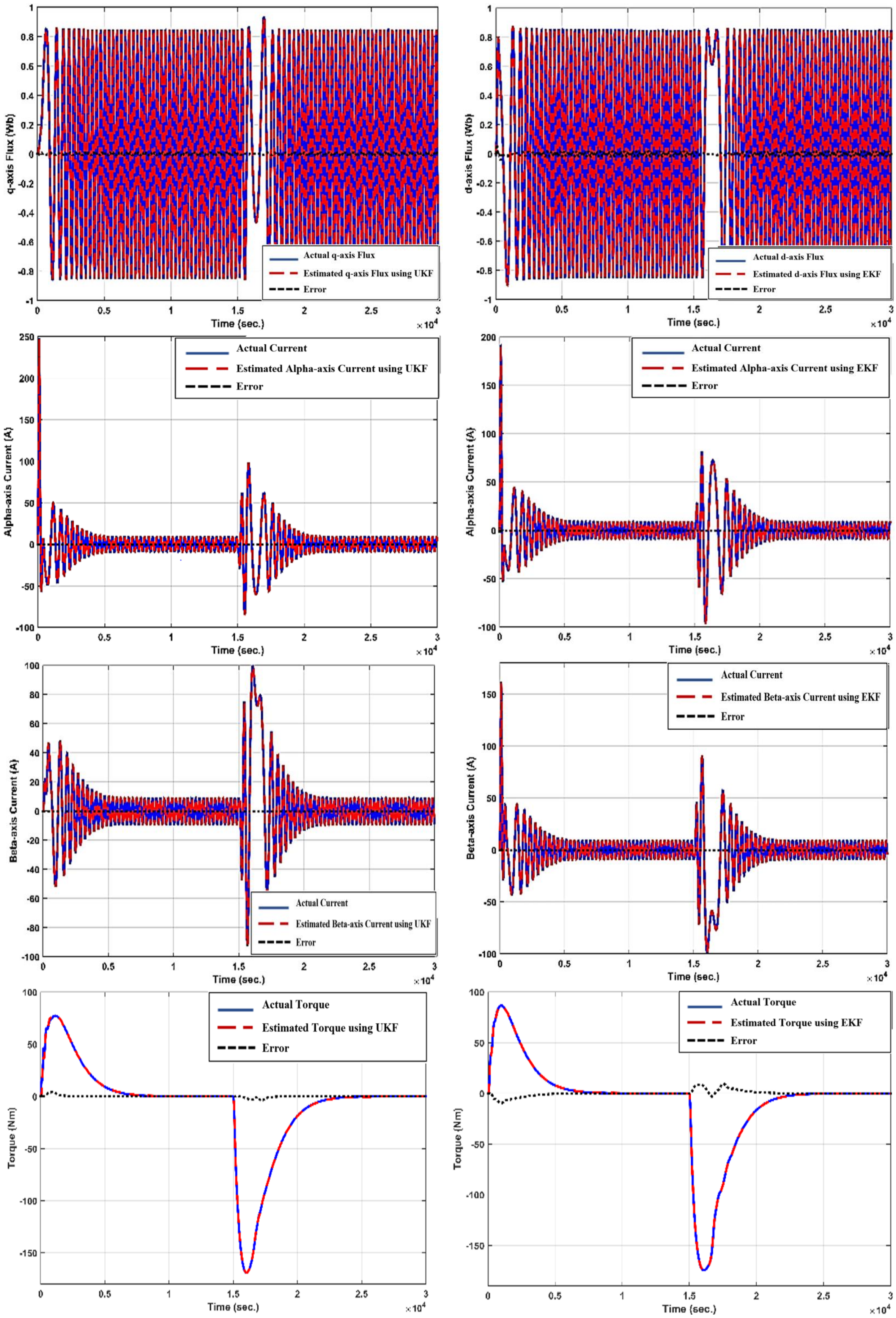
This paper proposed a method to optimize EKF and UKF for estimation speed, flux, torque, and current in sensorless DFOCIM drive. Multi objective genetic algorithm was used to find the optimal selection of state and noise covariance matrices in both EKF and UKF. The main objective in multi objective genetic algorithm to be minimized ware MSE of speed, current, and flux. Senserless DFOCIM drive was presented to achieve the decoupling between torque and flux based on optimized EKF and optimized UKF. The optimized EKF and UKF provided the accurate estimation of speed, flux, torque, and current in DFOCIM drive. Furthermore, optimized UKF had high accuracy of state estimations than optimized EKF. According to our expectations, the optimal control parameters of DFOC drive will be studied to find the optimal control of senserless DFOCIM drive.

APPENDIX



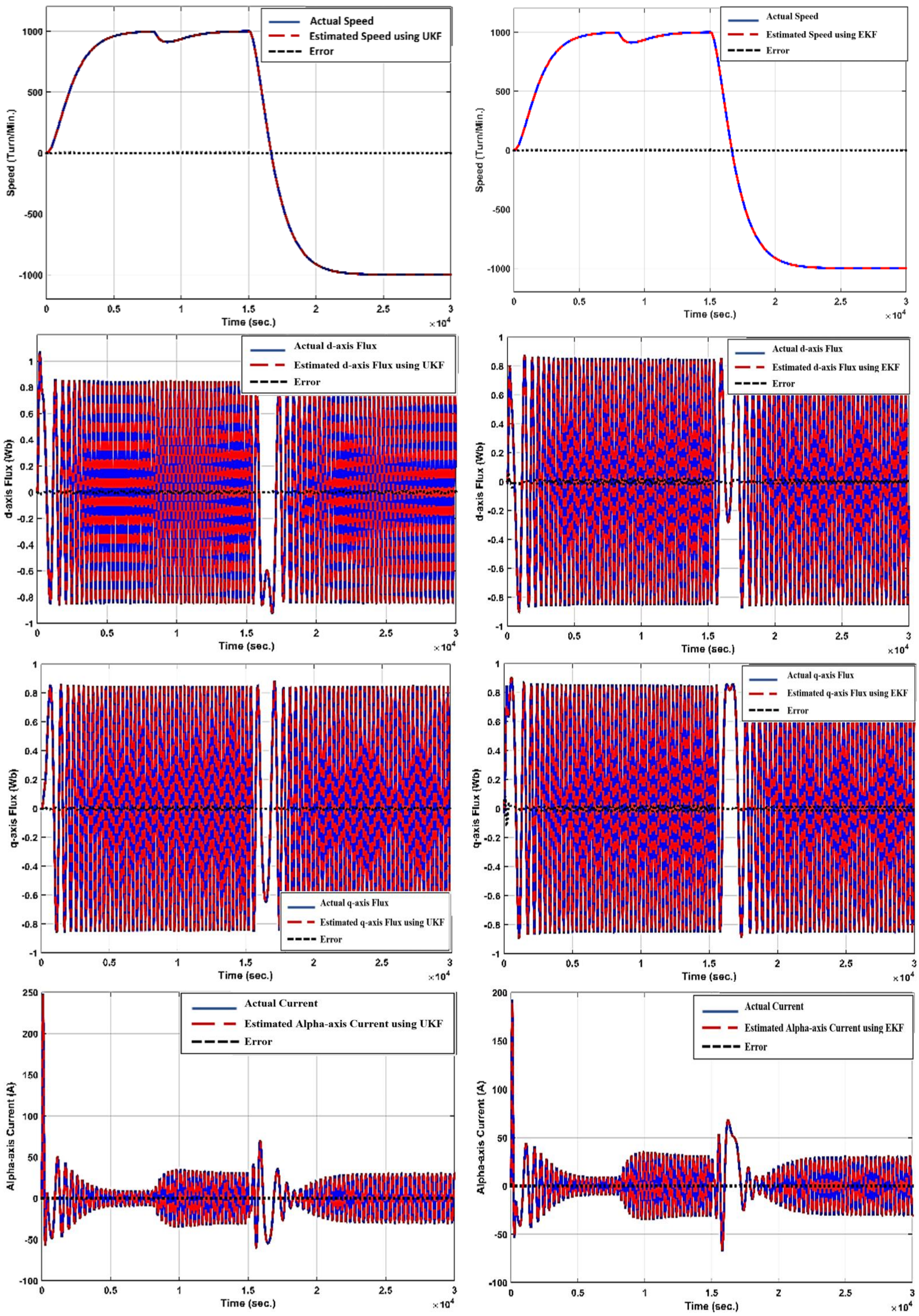
(a) (b)

Figure 2. Comparison in No-load condition between (a) optimized UKF and (b) optimized EKF in DFOCIM drive (*continue*)



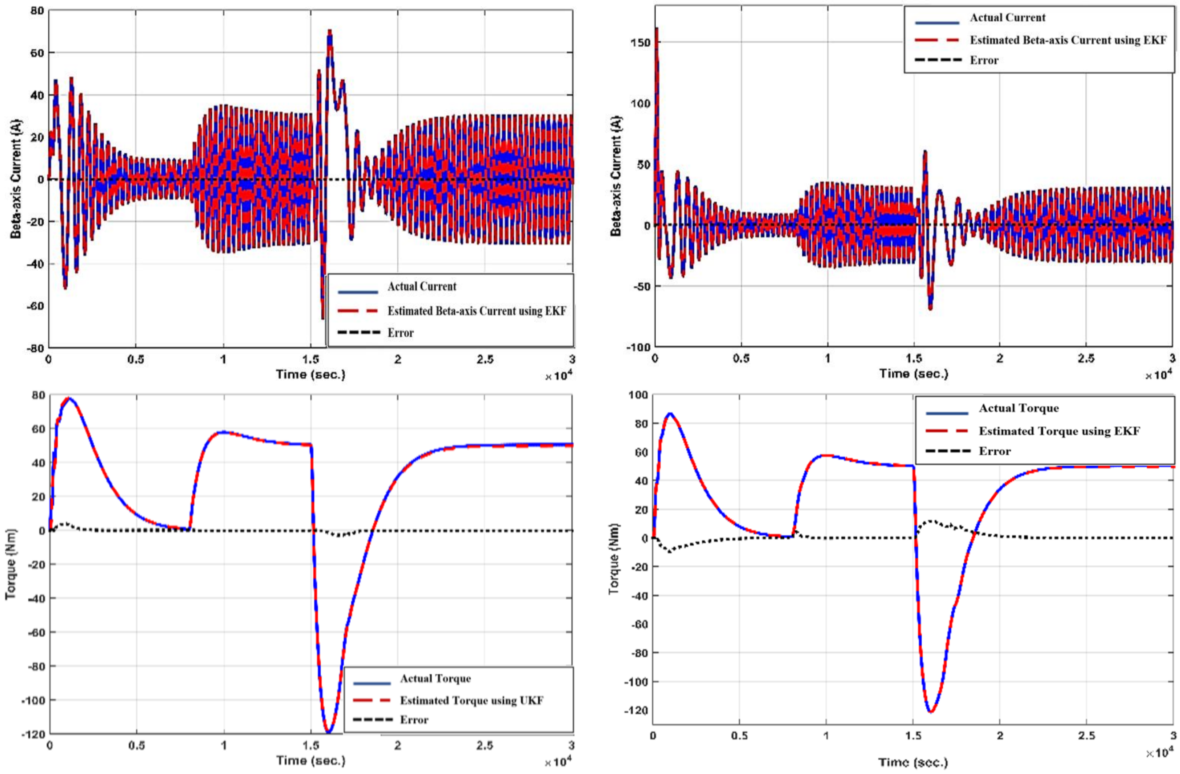
(a) (b)

Figure 2. Comparison in No-load condition between (a) optimized UKF and (b) optimized EKF in DFOCIM drive



(a) (b)

Figure 3. Comparison in load condition between (a) optimized UKF and (b) optimized EKF in DFOCIM drive (*continue*)



(a) (b)

Figure 3. Comparison in load condition between (a) optimized UKF and (b) optimized EKF in DFOCIM drive

Table 4. Comparison in MSE of optimized UKF and optimized EKF

Estimation	No-load tracking		Load tracking	
	UKF	EKF	UKF	EKF
Speed	0.3159	9.0947	0.6871	13.4
current	2.053e-21	0.0016	2.94e-21	0.0016
Flux	8.08e-05	3.22e-04	7.59e-05	3.11e-04
Torque	0.0462	0.7830	0.0462	0.9032

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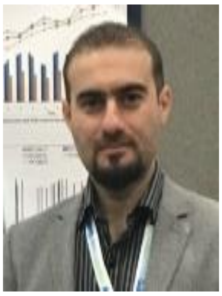
BIOGRAPHIES OF AUTHORS

Mohammed Khalil Hussain received his B.Sc. and M. Sc. degrees in electrical power engineering from College of Electrical and Electronic Technology, Baghdad, Iraq, in 2005 and 2008, respectively. He received his Ph.D. degree from the Department of Electrical and Computer Engineering of Western Michigan University, United states in 2018. The research interests include power system transients, optimization of power components, electromagnetic compatibility, and Kalman filters. He can be contacted at email: mohammedkhalil@uobaghdad.edu.iq.

Bajel Mohammed Alshadeedi received the B.Eng. degree in mechanical engineering from university of Tikrit, Iraq in 2006. M.Sc. Degree was received from the Department of Industrial and Entrepreneurial Engineering and Engineering Management of Western Michigan University, United states in 2016. The research interests include optimization algorithms and life cycle cost. She can be contacted at email: bajelmohammed@yahoo.com.



Rashid Hejeejo received his B.Sc. and M.Sc. degrees in electrical power engineering from College of Electrical and Electronic Technology, Baghdad, Iraq, in 2006 and 2009, respectively. He received his Ph.D. degree from University of Newcastle, Australia in 2017. Current research interests include Sustainable energy, Smart Grid, Microgrid, Renewable energy management and POS program. He can be contacted at email: rashidhameed58@yahoo.com.