Volume 9, Issue 3
June 2020

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

An Optimized Extended Kalman Filter for Indirect Vector Control of Induction Motor

[1]Jyothilakshmi M S, [2]Uma Syamkumar, [3]Amal Sasi

[1]Department of Electrical Engineering, Government Engineering College, Thrissur

[2]Department of Electrical Engineering, Government Engineering College, Thrissur

[3]Department of Electrical Engineering, Government Engineering College, Thrissur

E-mail: [1]jyothilakshmi513@gmail.com, [2]uma@gectcr.ac.in, [3]amalsasi@outlook.com

ABSTRACT

In this study an optimized extended Kalman filter is used for indirect vector control of induction motors. An extended Kalman filter provides an observer based vector control scheme for induction motors. A Population-based optimization algorithm called Differential evolution algorithm is used for the optimization of extended Kalman filter. The calculated errors between measured and estimated current components are utilized for the DEA based optimization process. DEA based optimization is done to obtain accurate and optimized noise covariance matrices. This ensures efficient performance of EKF in the estimation of states. An offline DEA optimization is done and simulation results for the speed estimation in an induction motor are presented and analyzed.

1. INTRODUCTION

In most of the applications of induction motors, vector control scheme takes a major role. In conventional vector control schemes, the rotor speed is used as a feedback for control. For providing this closed loop control the speed or position is measured using shaft encoders. While using these types of measurements some of the difficulties may arise. It is expensive to use encoders and other measurement techniques for this purpose and also they did not guarantee system reliability.

Speed sensorless control of induction motors provides an efficient way of vector control by eliminating the speed measurement devices and their associated connections. Speed sensorless control techniques when applied to induction motors,they provide advantages like lower cost, ruggedness and higher reliability.

Kalman filter acts as an observer in the noisy environment and provides an efficient way for the state estimation. Estimation of states from process and system noise is possible only if the covariances of these noises are well known.

In addition to current and flux states if rotor speed is included in a non-linear model of induction motor it becomes an extended induction motor model. Based on this extended motor model an EKF can perform the operations of state estimation. For an accurate and reliable estimation of states, EKF algorithm demands covariance matrices of noises in the system. In conventional cases trial and error methods are used for this purpose. Being a time consuming process and also due to inaccuracy, modern methods are adopted for the optimization of these matrices.

In this study a DEA based optimization technique is used for the optimization of noise covariances. Estimation of states like I_{ds}, I_{qs}, F_{ds}, F_{qs} and w_r are done using EKF algorithm for speed sensorless indirect vector control of induction motor. The EKF is optimized using DEA with mean squared current error as the objective signal. Simulation studies for the speed estimation of induction motor using EKF algorithm via DEA optimization is presented.

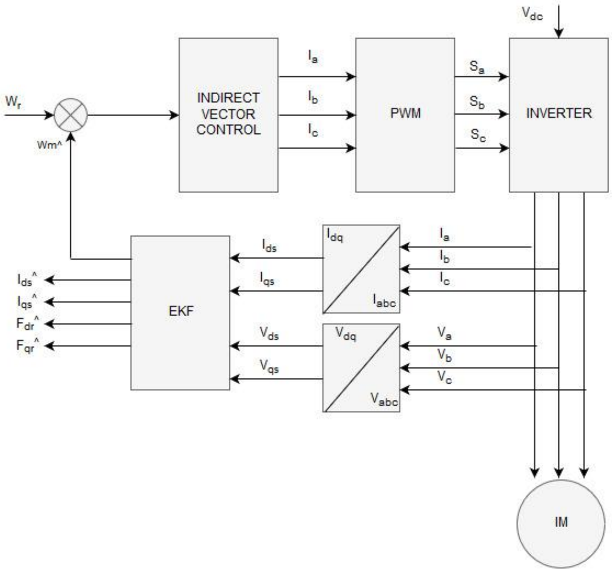


Fig.1. Indirect Vector Control of IM Using EKF Algorithm

Fig.1. shows the schematic diagram for indirect vector control of induction motor using EKF algorithm. The voltage and current sensors gives the sensed quantities like current and voltage. It is the input for EKF algorithm. This algorithm gives the estimated states like current components, flux and speed. This estimated speed will act as the feedback signal for entire indirect vector control scheme and successfully eliminates the use of speed encoders.

2. EXTENDED INDUCTION MOTOR MODEL

The extended state model of induction motor is taken and the EKF algorithm is designed. For the estimation of states like currents, flux and speed sensorless control of induction motor a rotor or stator flux model of the motor is usually taken. The estimation equations are as follows:

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

$$\dot{x}(t) = f\big(x(t), u(t)\big) + w_1(t)$$

$$= Ax(t) + Bu(t) + w_1(t) \qquad (1)$$

$$z(t) = cx(t) + w_2(t)$$
$$= Cx(t) + w_2(t) \qquad (2)$$

The matrix representation based on rotor flux model of induction motor is given below:

$$\begin{bmatrix} \dot{i}_{ds} \\ \dot{i}_{qs} \\ \dot{f}_{ds} \\ \dot{f}_{qs} \\ \dot{w}_r \end{bmatrix} = \begin{bmatrix} -\left(\frac{R_s}{L_z} + \frac{(R_r L_m{}^2)}{L_r{}^2 L_z}\right) & 0 & \frac{R_r L_m}{L_r{}^2 L_z} & \frac{L_m p w_m}{L_z L_r} & 0 \\ 0 & -\left(\frac{R_s}{L_z} + \frac{(R_r L_m{}^2)}{L_r{}^2 L_z}\right) & -\frac{L_m p w_m}{L_z L_r} & \frac{R_r L_m}{L_r{}^2 L_z} & 0 \\ \frac{R_r L_m}{L_r} & 0 & -\frac{R_r}{L_r} & -P w_m & 0 \\ 0 & \frac{R_r L_m}{L_r} & p w_m & -\frac{R_r}{L_r} & 0 \\ -\frac{3}{2}\frac{p}{J}\frac{L_m}{L_r} f_{ds} & \frac{3}{2}\frac{p}{J}\frac{L_m}{L_r} f_{qs} & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{ds} \\ i_{qs} \\ f_{ds} \\ f_{qs} \\ w_r \end{bmatrix} + \begin{bmatrix} \frac{1}{L_z} & 0 \\ 0 & \frac{1}{L_z} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_{ds} \\ v_{qs} \end{bmatrix} + w_1$$

$$\begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{ds} \\ i_{qs} \\ f_{ds} \\ f_{qs} \\ w_r \end{bmatrix} + w_2$$

x: Extended state vector, f : Non linear function of states and inputs, A : System matrix, u : Control input vector, B : Input matrix , w_1 and w_2 : Process and measurement noise, c : function of outputs, C : Measurement matrix, p: number of poles, L_z: stator transient inductance, R_s and R_r: stator and rotor resistance, L_s and L_r: Stator and rotor inductance, i_{ds} and i_{qs}: components of stator current, f_{ds} and f_{qs}: components of rotor flux, w_r: rotor speed, J: inertia of motor.

3. EKF ALGORITHM

Development of EKF algorithm is based on extended induction motor state model. The mathematical equations involved in the Kalman filter algorithm takes the non-linear extended model of induction motor to obtain the state estimation process. . The equations (3)-(4) is discretized and linearized to form state equations using EKF algorithm. The discretized equations can be written as follows:

$$x(k+1) = f\big(x(k), u(k)\big) + w_1(k) \qquad (3)$$
$$z(k) = Cx(k) + w_2(k) \qquad (4)$$

Since Kalman filter is not applicable to non-linear problems and an EKF needs to be developed. The linearized model can be obtained as:

$$F(k) = \frac{\partial f\big(x(k), u(k)\big)}{\partial x(k)} \qquad (5)$$

Mathematical Equations in EKF algorithm can be summarized as:

$$s(k) = F(k)P(k)F(k)^T + Q \qquad (6)$$
$$P(k+1) = s(k) - s(k)C^T \times (R + Cs(k)C^T)^{-1} Cs(k) \qquad (7)$$
$$K = P(k+1)C^T R^{-1} \qquad (8)$$
$$\hat{x}(k+1) = \hat{f}\big(x(k), u(k)\big) + K \times \big(z(k) - C\hat{x}(k)\big) \qquad (9)$$

Q: Covariance matrix of system noise
R: Covariance matrix of output noise

EKF algorithm consists of two set of equations called time update equations and measurement update equations. The first stage is time update which is also called prediction stage. In this stage the Kalman gain K is calculated. After that the actual process is measured to find z(k) and by using that a state estimate is predicted. The next stage is measurement update which is also called correction stage. Here the sum of the predicted state and the correction term multiplied with Kalman gain K gives the next estimated state x(k+1).

4. OPTIMIZED EKF ALGORITHM

Differential Evolution Algorithm

DEA is a global optimization algorithm which slightly resembles to genetic algorithm in operations. DEA also involves three operations called mutation, crossover and selection like GA. DEA works with randomly generated initial population. The first step in DEA is selecting a vector from the initial population called target vector. Second stage is to create a trial vector. In order to generate a trial vector, three of the solution vectors are selected randomly from the initial population and they are combined to form a new solution vector called mutant vector. This mutant vector is generated by using a mathematical formula $M=X_1 + f(X_2-X_3)$. Here f is a constant and X_1, X_2 and X_3 are three random vectors of solution. After the creation of mutant vector it is crossed over with initially chosen target vector to form a trial vector. The

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

last step in DEA is the selection between these target vector and trial vector. The vectors with better fitness values are selected for next cycle.

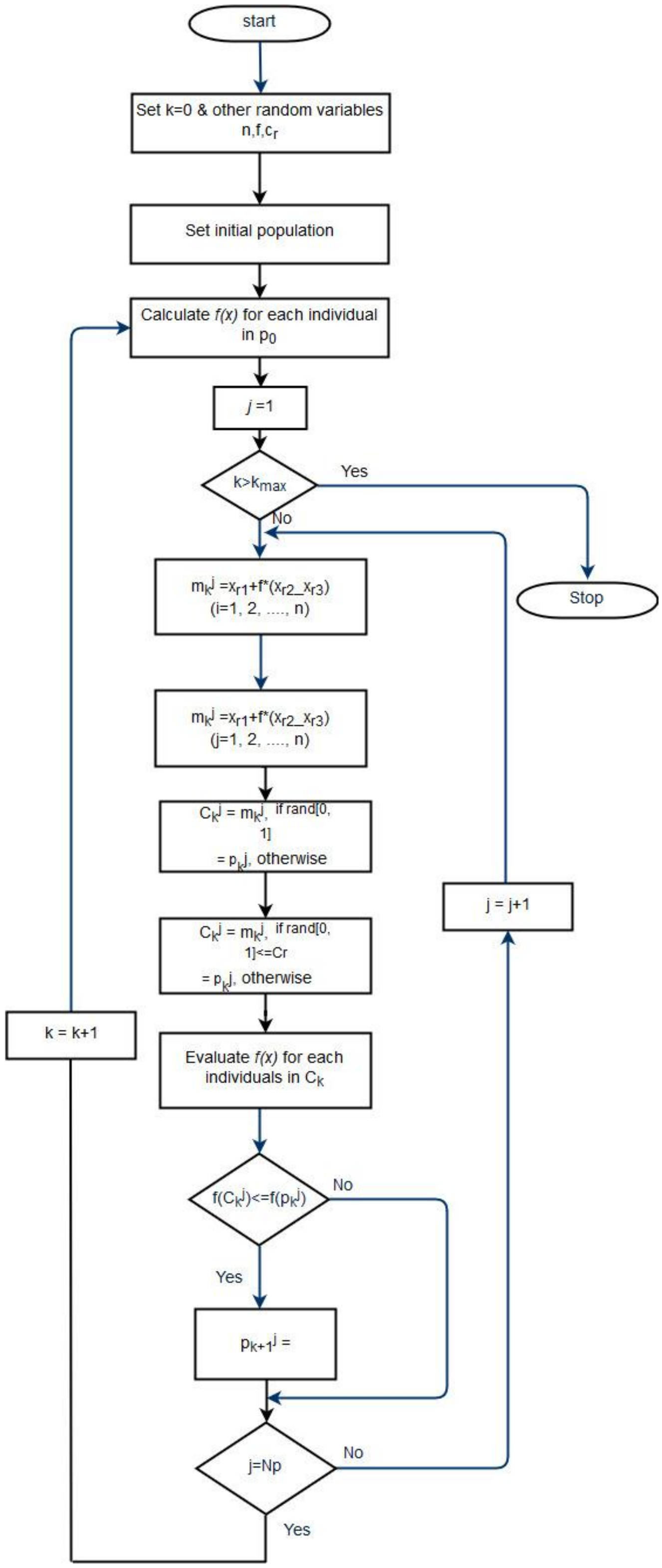


Fig.2. Flow chart for DEA

Optimization Using DEA

For the successful estimation of states in speed sensorless control of induction motor using EKF algorithm most important part is the minimization and optimization of error covariance of the estimation. Mainly we have to optimize the two matrices Q and R. System noise covariance matrix is a 5×5 diagonal matrix and consists of 3 parameters to be optimized. The measurement noise covariance matrix R consists of only one parameter for optimization with a 2×2 diagonal matrix form.

$$Q = \begin{bmatrix} q_i & 0 & 0 & 0 & 0 \\ 0 & q_i & 0 & 0 & 0 \\ 0 & 0 & q_f & 0 & 0 \\ 0 & 0 & 0 & q_f & 0 \\ 0 & 0 & 0 & 0 & q_w \end{bmatrix}$$

$$R = \begin{bmatrix} r_{noise} & 0 \\ 0 & r_{noise} \end{bmatrix}$$

Here q_i, q_f and q_w are called parameters of modeling errors and r_{noise} is the parameter related to output noise. These are the 4 parameters to be optimized using DEA. The objective function used for the optimization process is the sum of mean squared error, which is obtained by taking the difference between measured and estimated states if currents. The objective function is as follows:

$$f(x) = \frac{1}{N}\sum_{n=1}^{N}\left(i_{ds} - \widehat{i_{ds}}\right)^2 + \left(i_{qs} - \widehat{i_{qs}}\right)^2 \quad (10)$$

Offline Optimization Process

Flow chart of optimization process used in this work is given in the fig.2. A D-dimensional vector can represent an optimization job composed of D parameters. At the beginning, a population of NP solution vectors is developed randomly in DE. By implementing mutation, crossover and selection operators, this population is effectively enhanced. P_k is the initial population. It can be also termed as solution vector. M_k^j and C_k^j are the two populations after mutation and crossover respectively.The population size is denoted by np and g being a constant factor which provides the control over differential variations. Cr is the cross over rate and f(x) denotes the fitness function. The entire code for DEA based optimization is simulated in MATLAB. Optimization of the parameters is done offline using the collected real time measurements of machine voltage and currents.

Sl No	Noise Covariance Parameters	Values
1	q_i	5.6×10^{-5}
2	q_f	5.97×10^{-5}
3	q_w	5.33×10^{-5}
4	r_{noise}	20

Table.1. DEA Optimized Noise Covariance Matrix Parameters

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

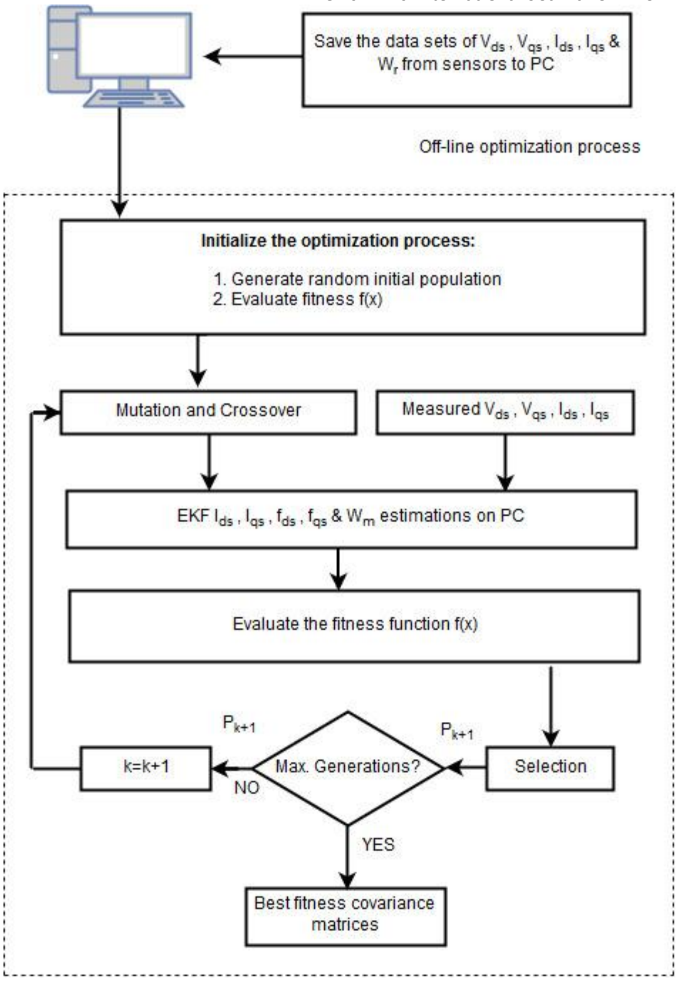


Fig.3. Block diagram for Indirect Vector Control of IM Using EKF Algorithm

5. SIMULATION STUDY

The tuning of noise covariance matrices are done by differential evolution algorithm. By using DEA more accurate estimation of states are made possible rather than the traditional trial and error concept.

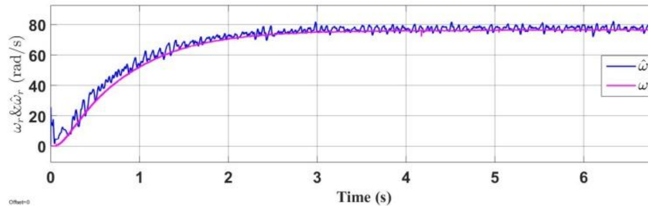


Fig.4. Measured and estimated speed of induction motor using EKF

The simulation result for the estimated speed using DEA optimized EKF algorithm is shown in fig.4. Fig.5 and 6 shows the waveforms for estimated as well as measured components of stator current.

Simulation for speed estimation of induction motor using EKF algorithm is done using MATLAB software.

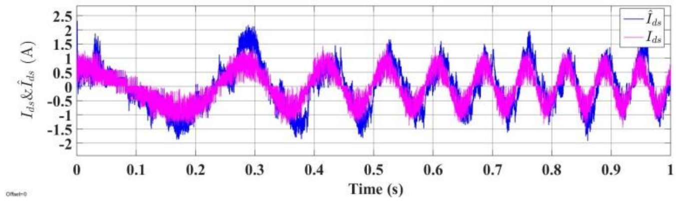


Fig.5. Measured and estimated current component i_{ds}

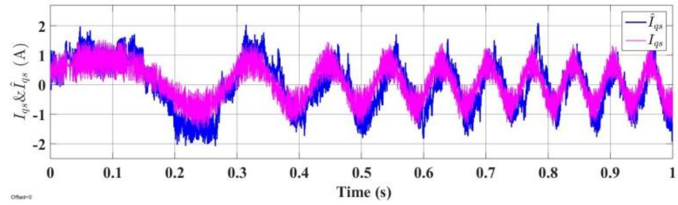


Fig.6. Measured and estimated current component i_{qs}

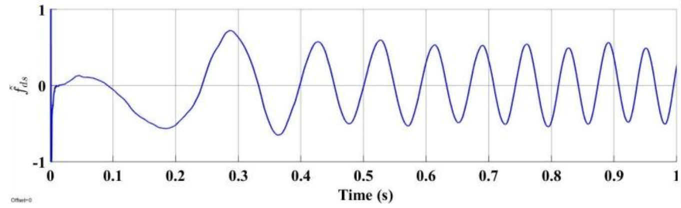


Fig.7. Estimated flux component f_{ds}

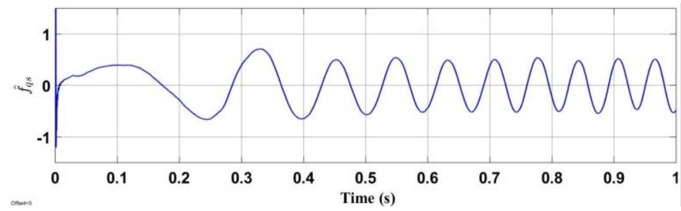


Fig.8. Estimated flux component f_{qs}

An extended Kalman filter functions like an observer and estimates the states like current, flux and speed. Through these estimation of states it can also be used for the speed sensorless direct vector control of induction motor.

6. HARDWARE IMPLEMENTATION

Speed sensorless vector control of induction motor using an optimized EKF algorithm is simulated and the results were analysed in the previous chapter. To practically verify the simulation results, the sensorless drive is implemented using the NI card (PCIe-6351), inverter stack, voltage and current sensor board and an induction motor.This chapter contains the detailed description of all the devices used in the hardware implementation. It also describes the overall experimental setup and results obtained. For the hardware implementation NI card PCIe-6351 from National Instruments is used. It acts as an interface for the complete control. The optimized EKF algorithm is implemented on this power PC-based NI card. An inverter stack is used to feed the 3 phase induction motor. A sensor board from Entuple technologies is used for measuring the phase voltages and currents. The speed encoder is used only for the validation of speed. The block diagram for complete hardware set up is shown in Figure 9.

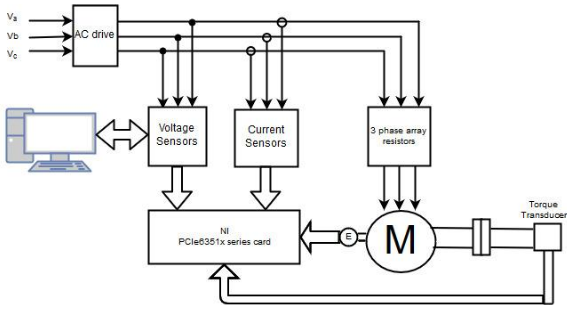
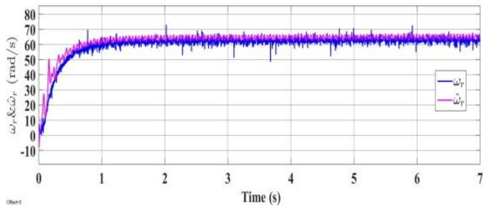


Fig.9. Block Diagram of Speed Sensorless Vector Control of IM Using EKF

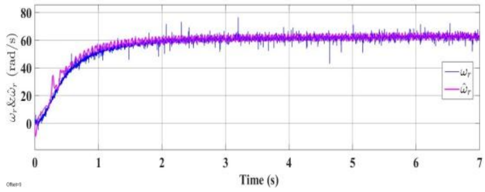
Experimental Results

- Online Estimation of States With EKF Algorithm

The Sensed phase voltages and currents are given as analog inputs and the generated pulses are taken as digital outputs. The extended kalman filter estimates the states like speed, stator currents and rotor fluxes. The estimated speed can be used for the speed sensorless indirect vector control of induction motor.



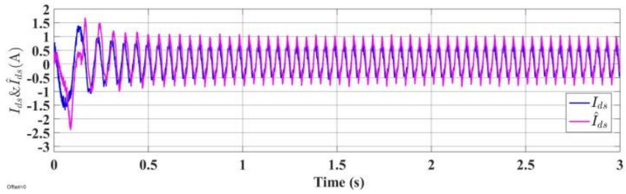
(a)Unoptimized EKF



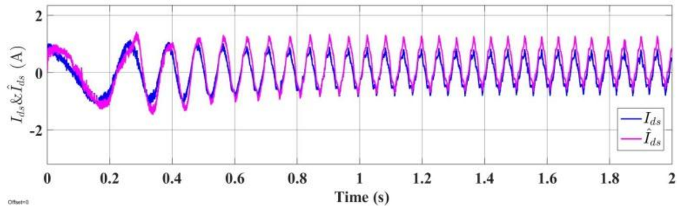
(b)Optimized EKF

Fig.10. Measured and Estimated Speeds of Induction Motor

Fig.10 shows measured and estimated speed of induction motor with optimized as well as unoptimized EKF algorithm. The estimated speeds are compared with the corresponding machine speeds. Here the reference speed is given as 65 rad/s. In unoptimized EKF algorithm, the estimated speed is slightly greater than the reference speed. It is around 69 rad/s. While using an optimized EKF algorithm the estimated and measured speed is almost similar.



(a) Unoptimized EKF

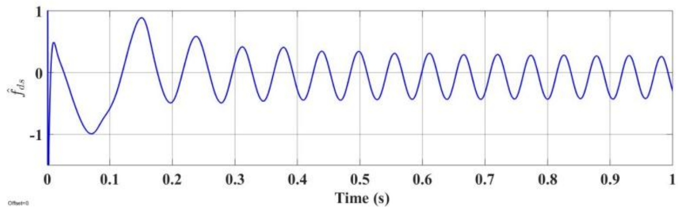


(b)Optimized EKF

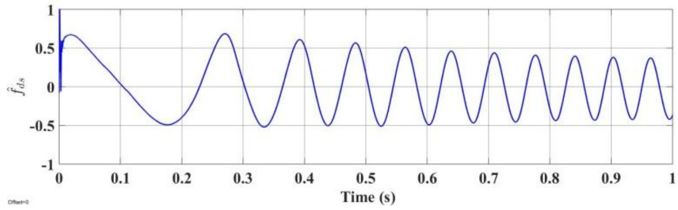
Fig.11. Measured and Estimated Currents of Induction Motor

Figures 11 to 13 shows the results of estimated currents and flux components for unoptimized and optimized EKF algorithm.

Estimated current with optimized EKF almost traces the original measured current while in unoptimized EKF algorithm, the current magnitude is slightly higher.

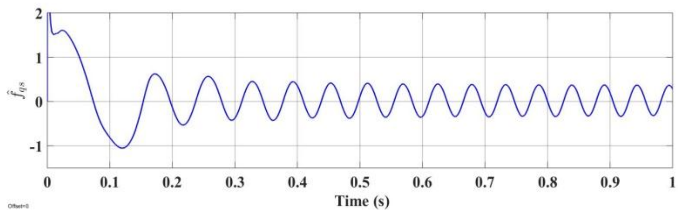


(a)Unoptimized EKF

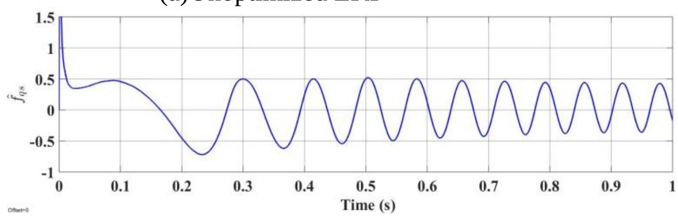


(b)Optimized EKF

Fig.12. Estimated Flux Component f_{ds}



(a)Unoptimized EKF



(b)Optimized EKF

Fig. 13. Estimated Flux Component f_{qs}

7. CONCLUSION

The vector control of induction motor is made possible without the use of speed sensors. Only by the measurement of motor phase voltages and currents the entire indirect vector control scheme is performed. The EKF algorithm needs only the sensed voltages and currents for the estimation of speed of

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

induction motor. In this project EKF acts as an observer for the speed estimation in speed sensorless control of induction motor. The state variables like stator currents, rotor fluxes and rotor speed can be estimated using an EKF algorithm with accuracy. A DEA based optimization is provided for optimizing the noise covariance matrices to get successful estimation of speed. Speed Sensorless vector control of induction motor is simulated in MATLAB/simulink environment and implemented using NI card PCIe-6351. Satisfactory simulation results are obtained in speed estimation of induction motor using EKF with DEA optimization. Thus performance of the drive is verified with both simulation and experimental results.

REFERENCES

[1] M. Barut and Emrah Zerdali, "The Optimization of EKF Algorithm based on Current Errors for Speed-Sensorless Control of Induction Motors" IEEE International Conference on Electrical Machines and Power Electronics, Sep. 2015.

[2] M. Barut, S. Bogosyan, and M. Gokasan, "Speed-Sensorless Estimation for Induction Motors Using Extended Kalman Filters," IEEE Transactions on Industrial Electronics, vol. 54, no. 1, pp. 272–280, Feb. 2007.

[3] V. Verma, C. Chakraborty, S. Maiti, and Y. Hori, "Speed Sensorless Vector Controlled Induction Motor Drive Using Single Current Sensor," IEEE Transactions on Energy Conversion, vol. 28, no. 4, pp. 938–950, Dec. 2013.

[4] Emrah Zerdali and M. Barut, "The Comparisons of Optimized Extended Kalman Filters for Speed-Sensorless Control of Induction Motors", IEEE Transactions on Industrial Electronics, vol. 64, no. 6, June 2017.

[5] M. G. Aydeniz and I. Senol, "A Luenberger-sliding mode observer with rotor time constant parameter estimation in induction motor drives." Turkish Journal of Electrical Engineering and Computer Sciences, vol. 19, no. 6, 2011.

[6] C. El Moucary, G. Garcia Soto, and E. Mendes, "Robust rotor flux, rotor resistance and speed estimation of an induction machine using the extended Kalman filter," in Proceedings of the IEEE International Symposium on Industrial Electronics, 1999. ISIE '99, vol. 2, 1999, pp. 742–746 vol.2.

[7] M. Barut, S. Bogosyan, and M. Gokasan, "Speed-Sensorless Estimation for Induction Motors Using Extended Kalman Filters," IEEE Transactions on Industrial Electronics, vol. 54, no. 1, pp. 272–280, Feb. 2007.

[8] M. Barut, R. Demir, E. Zerdali, and R. Inan, "Real-Time Implementation of Bi Input-Extended Kalman Filter-Based Estimator for Speed-Sensorless Control of Induction Motors," IEEE Transactions on Industrial Electronics, vol. 59, no. 11, pp. 4197–4206, Nov. 2012.

[9] K. L. Shi, T. Chan, Y. Wong, and S. Ho, "Speed estimation of an induction motor drive using an optimized extended Kalman filter," IEEE Transactions on Industrial Electronics, vol. 49, no. 1, pp. 124–133, Feb. 2002.

[10] N. Salvatore, A. Caponio, F. Neri, S. Stasi, and G. Cascella, "Optimization of Delayed-State Kalman-Filter-Based Algorithm via Differential Evolution for Sensorless Control of Induction Motors," IEEE Transactions on Industrial Electronics, vol. 57, no. 1, pp. 385–394, Jan. 2010.