

An Investigative Study into Observer based Non-Invasive Fault Detection and Diagnosis in Induction Motors

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Abstract—A new observer based fault detection and diagnosis scheme for predicting induction motors' faults is proposed in this paper. Prediction of incipient faults, using different variants of Kalman filter and their relative performance are evaluated. Only soft faults are considered for this work. The data generation, filter convergence issues, hypothesis testing and residue estimates are addressed. Simulink model is used for data generation and various types of faults are considered. A comparative assessment of the estimates of different observers associated with these faults is included.

Keywords—Extended Kalman Filter, Fault detection and diagnosis, Induction motor model, Unscented Kalman Filter

I. INTRODUCTION

THIS conventional Fault Detection and Diagnostic (FDD) methods to identify faults in electric machines make use of MCSA (motor current signature analysis), noise and vibration monitoring and acoustic noise measurements [1]. MCSA is a knowledge based approach wherein the stator currents are acquired for a time window and the FFT is computed. Peaks observed in different frequency bands are indicative of various types of faults, which can be identified with the help of a look-up table [2]. However, MCSA method is not effective in case of variable frequency drives [3]. Acoustic noise and vibration based fault detection have limitations as they are sensitive to motor alignments, natural frequency of foundation and location of installation.

In this paper, a model based fault detection and diagnostics methodology is proposed, wherein a 5th order state variable model in d - q stationary reference frame, with I_{ds} , I_{qs} , ψ_{dr} , ψ_{qr} and ω as the state variables, is used [4]. The advantage of this model is that it requires minimum information of the machine parameters such as stator and rotor inductances, resistances, and mutual inductance, which can be computed using standard no load and blocked rotor tests on induction machines.

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Model based fault detection methods use appropriate transformations and deploy stochastic observers. The difference between estimated state variables (computationally obtained) and actual measurements, termed residues, obtained thereof provide the information required to judge the deviation of these residues from their healthy Gaussian white noise. The variations in the residues thus generated, by one or a combination of parameters and state estimates, are used for characterizing different type of faults.

The main benefit of model-based approach is that the existing inputs and information can be utilised for observer processing without the need for additional sensors. However, an accurate and simple mathematical model needs to be used which takes care of non-linear dynamics of induction motors and sometimes non-Gaussian uncertainties. A comparative assessment on the use of Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF) and Central Difference Kalman Filter (CDKF) for fault detection and diagnosis of induction machines has been attempted and the same is presented. Suitable detection techniques, having the capability of decoupling the impacts of disturbances and other measured inputs on fault signatures, are also addressed.

II. OBSERVER BASED METHODS : ADVANTAGES AND LIMITATIONS

The state space motor model chosen for this study comprises five states. They are direct and quadrature axis stator currents (I_{ds} , I_{qs}) direct and quadrature axis rotor fluxes (ψ_{dr} , ψ_{qr}) and the rotor speed (ω). The proposed algorithm is based on state observers (EKF, UKF and SRUKF) all of which can accommodate measurement uncertainties (noise) and model inaccuracies [5]. This study compares the relative performance of various observers applied to an induction motor. However, the limitation of any state observer is that initial selection of covariance matrices is very important and convergence and stability depend on this selection. In addition, the model needs to satisfy controllability and observability criteria and the noise terms are assumed to be zero mean Gaussian.

A. Discrete time state variable model.

The discrete time state variable model, which is used for this work is,

$$X(k+1) = A_d X(k) + B_d U(k) \quad (1)$$

$$Y(k+1) = C_d X(k) \quad (2)$$

The state space representation involves K_R, K_L, T_R, L_m, L_r , which are machine parameters, expressed in convenient form to be used in "A" matrix where [4],

$$K_L = (1 - L_m^2 / (L_s L_r)) L_s \quad (3)$$

$$K_R = R_s + L_m^2 R_r / L_r^2 \quad (4)$$

$T =$ Sampling time, $T_R =$ Rotor time constant $= L_r / R_r$.

$$A_d = \begin{bmatrix} 1 - T \frac{K_R}{K_L} & 0 & T \frac{L_m R_r}{L_r^2 K_L} & T \frac{L_m \omega_r}{L_r K_L} & 0 \\ 0 & 1 - T \frac{K_R}{K_m} & -T \frac{L_m \omega_r}{L_r K_L} & T \frac{L_m R_r}{L_r^2 K_r} & 0 \\ T \frac{L_m}{T_r} & 0 & 1 - T \frac{1}{T_r} & -T \omega_r & 0 \\ 0 & T \frac{L_m}{T_r} & T \omega_r & 1 - T \frac{1}{T_r} & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (5)$$

$$B_d = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \quad (6); \quad C_d = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \quad (7)$$

Standard EKF equations taking Jacobian of 'A_d' matrix into account have been used in this paper for simulations. Relevant simulation results are also presented.

B. Simulink model for motor

A 'Simulink' model, as shown in Fig. 1 is used to simulate input parameters required for observer iterations. Two input voltages and two input currents in d-q axis are required to run observer iterations, which are generated from this model.

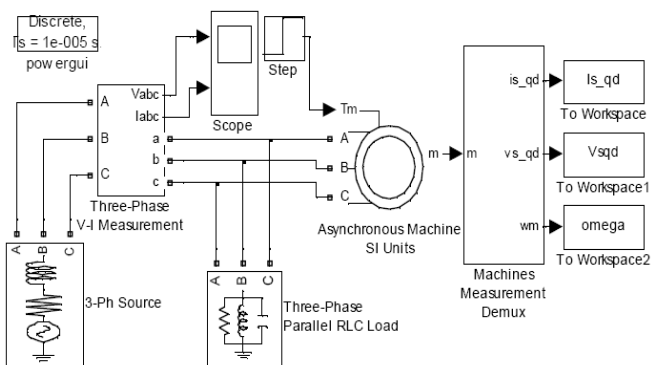


Fig. 1. SIMULINK model of induction motor used for simulations.

Fig. 2 shows the input voltage waveforms in *d-q* axis while Fig. 3 shows the *d-q* axis currents. Fig. 4 shows a typical *d*-axis current signal, corrupted with Gaussian white noise for the purpose of iterations in Kalman filter. The residue is calculated through iterations based on the difference between the predicted value and the measured value of any particular state – the *d*-axis stator current in this case. Once the corrected value is used for iteration instead of predicted value, a residue is generated. Any deviation from this white noise could be identified as an incipient fault.

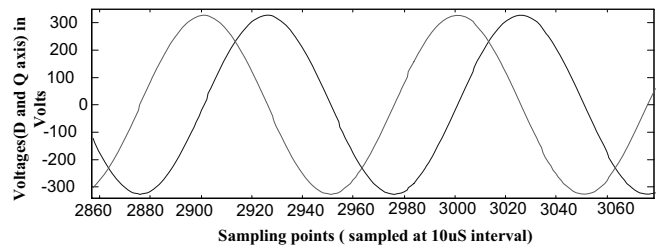


Fig. 2. *d* and *q* axis voltages as input to the model

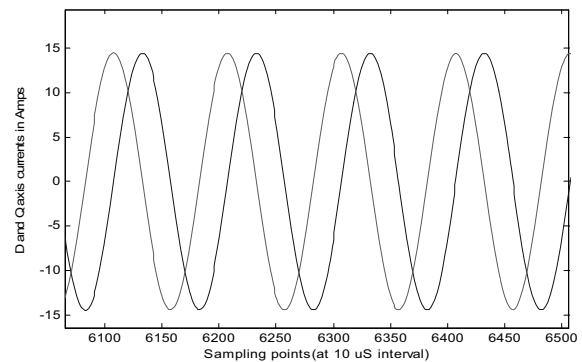


Fig. 3. *d* and *q* axis currents as input to the model

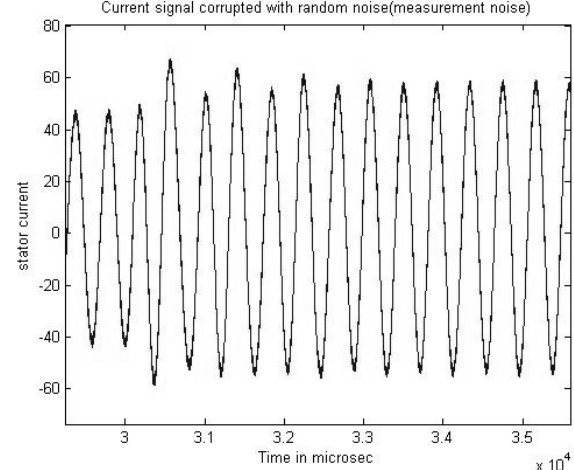


Fig. 4. Motor current signal with noise added.

A healthy motor is expected to have a residue, which is merely a white noise, with a mean zero, as can be seen from Fig. 5. Fig. 6 shows the estimated speed computed by EKF algorithm. The initial transients are attributed to transient currents during starting and observer response to these uncertainties.

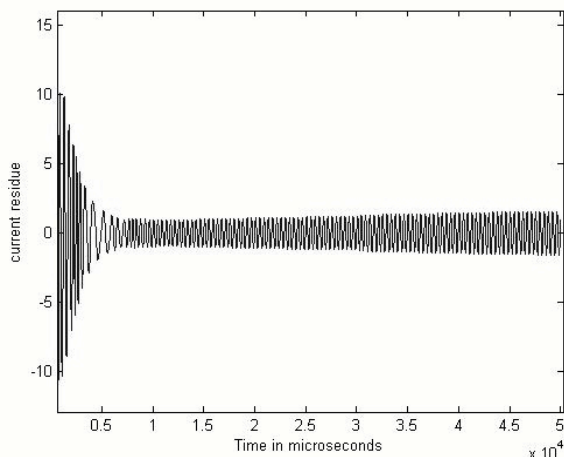


Fig. 5. Residue of motor current (healthy case).

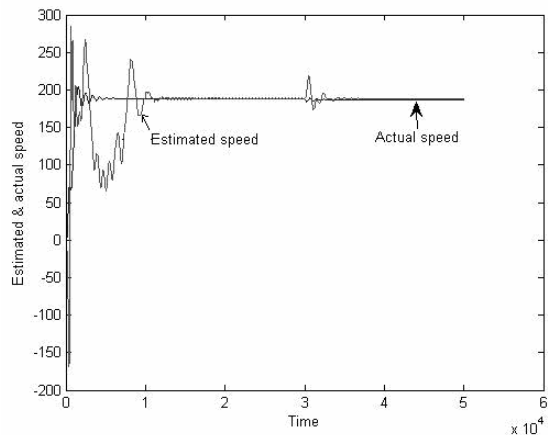


Fig. 6. The estimated and actual speed of motor

C. Simulations and results for various observers.

The model used for iterations is a 10hp, 400 V, 3-phase, 50 Hz asynchronous motor. Other machine parameters are given in Appendix A. All the four observers under consideration need two motor input voltages transformed into $d-q$ axis and two stator currents in $d-q$ axis. Other 'states' need not be known. The ReBEL[®] software toolkit version 0.2.7 along with MATLAB[®] is used for the iterations. Both KF and EKF have shown stable behavior in estimating states as shown in Fig 7 and 8. Results with UKF and its variant CDKF are shown in Figs. 8 and 9. In all cases, the same model and environmental parameters were passed and the results of Unscented Kalman filter (UKF) and Central Difference Kalman filter (CDKF) has not shown superior performance.

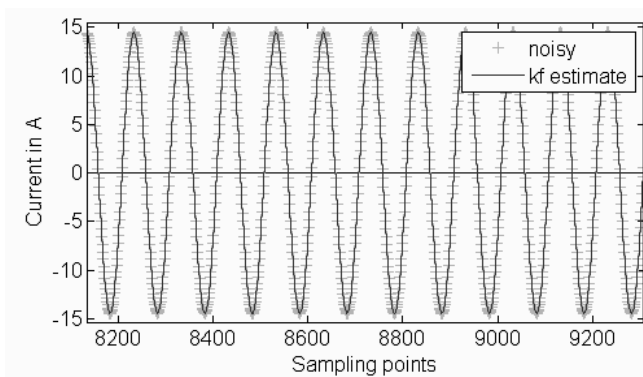


Fig. 7. KF Estimate of motor current.

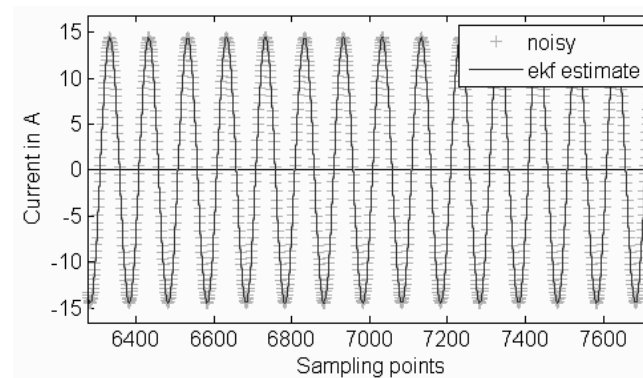


Fig. 8. EKF estimate of motor current signal.

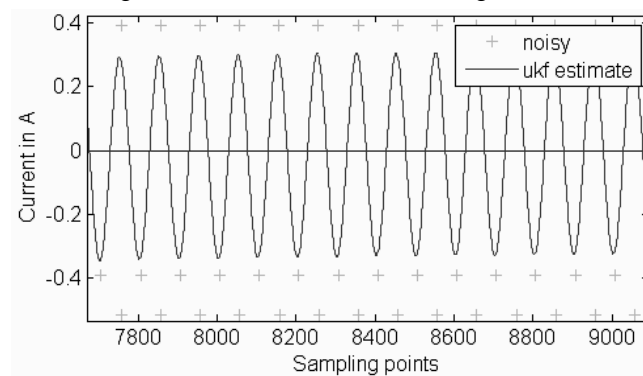


Fig. 9. UKF estimate of motor current signal

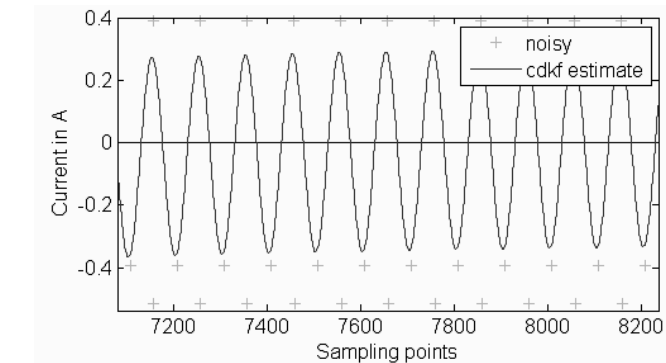


Fig. 10. CDKF estimate of motor current signal.

D. Faults

The faults considered here are soft faults such as a bias in current sensors, parametric variations in resistances or motor inductances, changes in unmeasured disturbances etc. A typical fault can be mathematically represented as [7]:

$$f = b_{f,i} e_{f,i} \sigma(k-t) \quad (8)$$

where f stands for the fault type, which can be any of the faults such as sensor fault (bias, f), actuator fault (bias, u), disturbance fault (d) or parameter fault (p). $b_{f,i}$ is the bias magnitude occurring at time t in the i^{th} sensor, $e_{f,i}$ is the fault vector with its i^{th} element equal to unity and all other elements equal to zero. t represents the time of occurrence of the fault and $\sigma(k-t)$ is the unit step function [7] defined as below:

$$\sigma(k-t) = 0 \text{ if } k < t \text{ and } = 1 \text{ if } k > t \quad (9)$$

If a bias of magnitude $b_{z,i}$ occurs at time t , in the i^{th} sensor, the output is given by,

$$Z(k) = H_x(k) + v(k) + b_{z,i} \sigma(k-t) \quad (10)$$

Similarly for bias magnitude of $b_{u,i}$ occurs in an actuator i at time t , is represented by,

$$u(k) = m(k) + b_{u,i} e_{u,i} \sigma(k-t) \quad (11)$$

E. Fault detection and Fault confirmation test

The test statistic, based on innovations at each time sample used for fault detection, is given by,

$$\varepsilon(k) = \gamma^T(k) V^{-1}(k) \gamma(k) \quad (12)$$

where $V(k)$ represents error covariance matrix and is computed as,

$$CP(k/k-1)C^T + R \quad (13)$$

The test statistic $\varepsilon(k)$ follows a central Chi-square distribution with n degrees of freedom. For any level of significance α , the test can be chosen from this distribution. A fault flag is set at any time, t when the test statistic $\varepsilon(k)$ exceeds the test criterion. The rejection of the null hypothesis by FDT at time t indicates that the fault may have occurred and a confirmation test is to be applied. On detection of a fault, in order to avoid a false alarm, a fault confirmation test is to be deployed. After N sampling instances, a confirmatory statistical test is done by making use of all innovations in the time $[t, t+N]$, as shown below.

$$\varepsilon(N, t) = \sum_{k=t}^{t+N} \gamma(k)^T V^{-1}(k) \gamma(k) \quad (14)$$

The occurrence of a fault at time t is confirmed if the test statistic $\varepsilon(N, t)$ exceeds the test criteria [7].

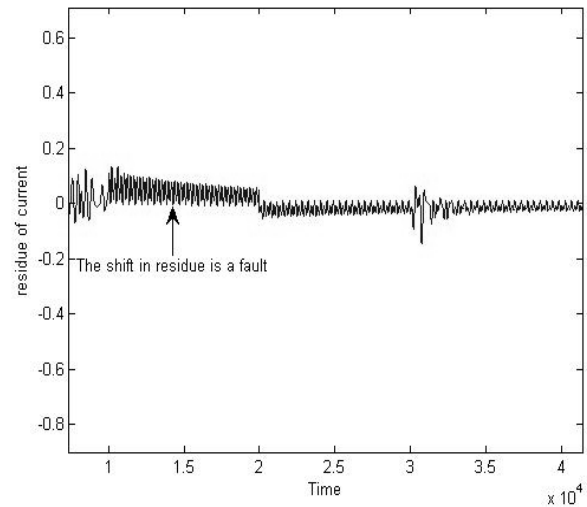


Fig. 11. Current signal residue under bias fault condition

Fig. 11 shows the residue of motor stator current with a current sensor fault. Fig. 12 shows the residue of induction motor with stator resistance increased. The shifts in both the cases are very distinct and can be identified from their respective fault signatures. Fig. 13 gives a comparative response of KF, EKF, UKF and CDKF to a step change in sensor current.

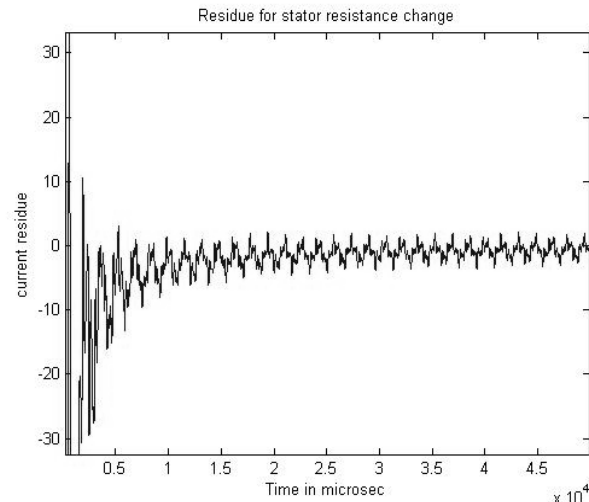


Fig. 12. Motor current signal residue with resistance change

Fig. 13 shows the performance of observers for the state estimation and Fig. 14 shows the relative performance to a fault in a current sensor. KF and EKF show a step change where as UKF and CDKF has given a slow response. Both linearised KF and EKF are able to predict the state (d -axis current) with better accuracy and have a faster response for bias fault in current sensor. On the other hand, UKF and CDKF have shown relatively slower response to the same bias fault.

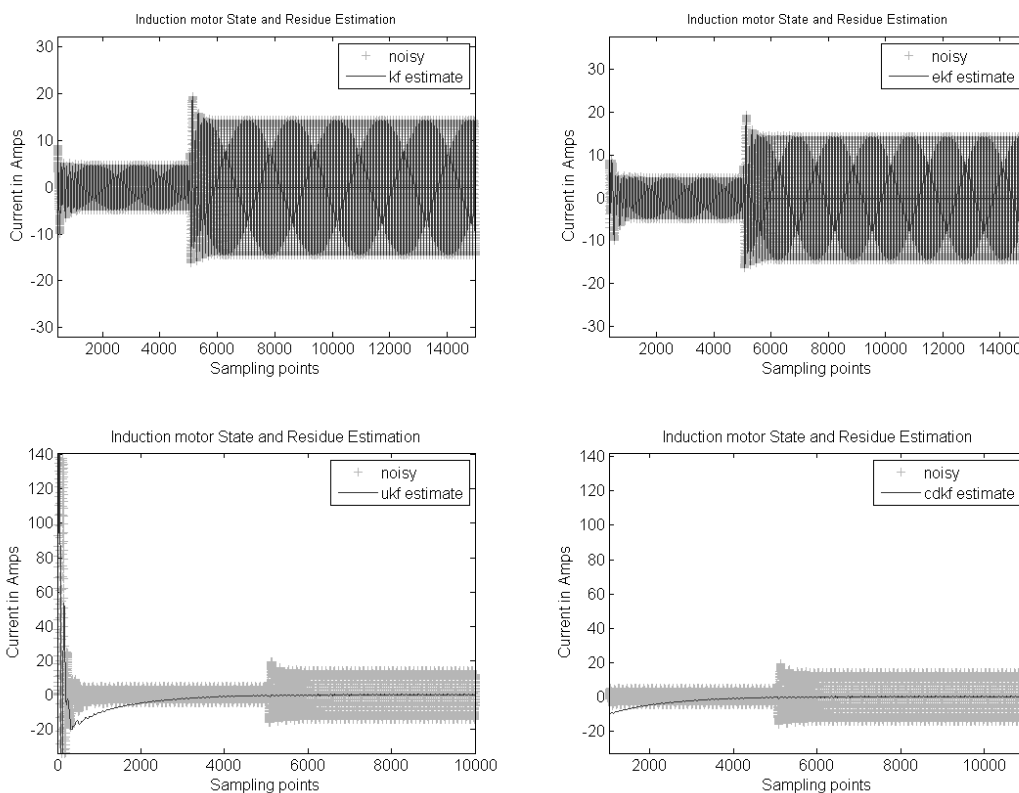


Fig. 13. KF, EKF, UKF and SRUKF as applied to state and residue estimation

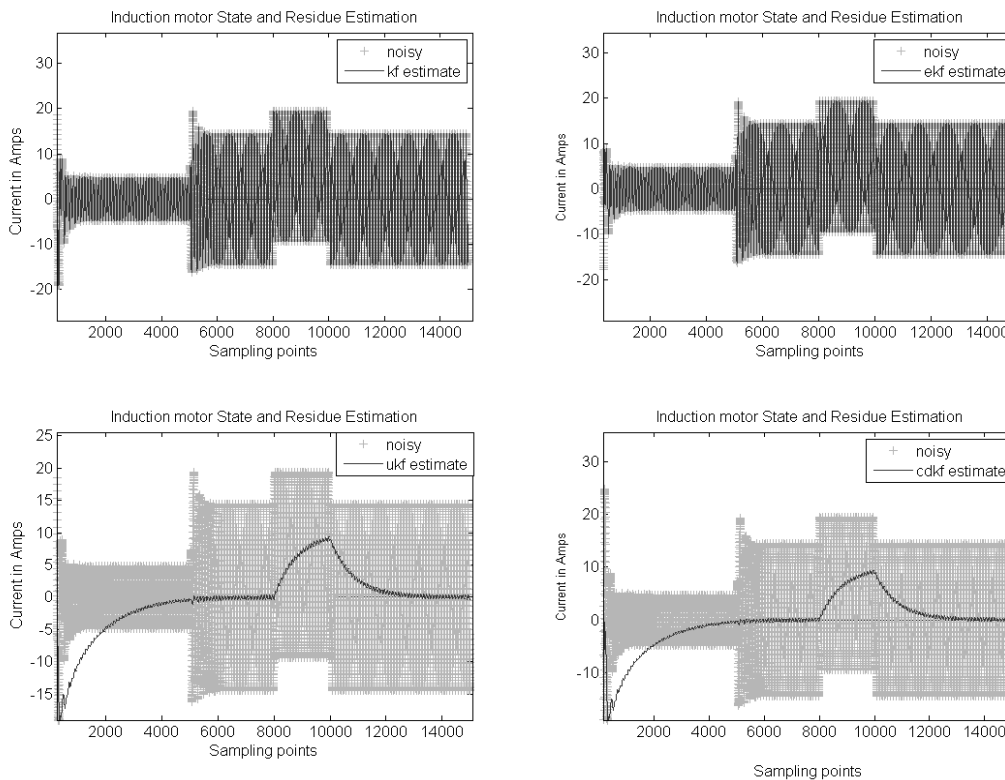


Fig. 14. KF, EKF, UKF and SRUKF response to a bias fault (current) in induction motor

III. CONCLUDING REMARKS

A comparative study on observer based fault detection and diagnosis in induction motors is presented in this paper, where a 5th order induction motor model is used with four different variants of Kalman filter. The shift in residues for current signal is used as the identification strategy. The type of fault is identified by the statistical correlations and the fault signatures. This method has the advantage that it takes care of model and measurement uncertainties, and is independent of input supply frequencies and supply variations. The model is machine specific and Kalman filter and its variants require extensive tuning to account for model uncertainties. This comparative study brings out the relative advantages of observers in fault detection and diagnosis domain and enables to select the right observer for this application.

NOMENCLATURE

V_{ds} :	d-axis stator applied voltage
V_{qs} :	q- axis stator applied voltage
I_{ds} :	d- axis stator current in stationary ref. frame
I_{qs} :	q- axis stator current in stationary ref. frame
ψ_{dr} :	d- axis rotor flux in stationary ref. frame
ψ_{qr} :	q- axis rotor flux in stationary ref. frame
ω :	Rotor speed
L_m :	Mutual inductance
L_s :	Stator self inductance
T_r :	Rotor time constant

Appendix - A

MOTOR DETAILS USED FOR SIMULATIONS

Motor rating: 10HP, 400Volts, 3 phase 50 Hz
Stator resistance: 0.7384 Ω
Stator inductance: 3.045 mH
Rotor resistance: 0.7402 Ω
Rotor inductance: 3.045mH
Mutual inductance: 0.1241mH
No of pair of poles: 2

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BIOGRAPHIES.

Padmakumar. S is presently working as Engineer in charge of electrical systems refurbishment cell, research reactor maintenance division, BARC. He is associated with electrical systems maintenance of nuclear research reactors. He graduated from Kerala Unuversity in 1985 and.completed his post gra graduation from IIT Bombay in 1987. He is Presently undergoing his Ph.D program at IIT Bombay.

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Kallol Roy completed his B.Tech (Electrical) from REC (NIT), Calicut in 1984. He obtained his M.Tech. (Electronics Design) from IISc., Bangalore in 1990 and PhD (System and Control) from IIT, Powai, Mumbai in 2000. He has been Post-Doctoral Fellow at University of Alberta, Canada, from April 2005 to March 2006. His expertise is in the Maintenance of Research Reactors, especially Planning, Retrofitting and Development of Predictive Maintenance tasks. His area of interest is Plant Performance Analysis through Mathematico-Statistical Techniques, Implementation of Fault Detection and Diagnosis Techniques at Equipment level and at plant level, by use of State Estimation (Kalman Filtering and Monte-Carlo Filtering) and Spectral Methods