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 \( I_s \), \( I_q \), \( \psi_d \), \( \psi_q \), and \( \omega \) 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.

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 (\( I_d, I_q \)) direct and quadrature axis rotor fluxes (\( \psi_d, \psi_q \)) and the rotor speed (\( \omega \)). 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,

\[
X(k+1) = A_T X(k) + B_T U(k)
\]

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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],

\[
K_L = \left( 1 - \frac{L_m^2}{L_s} \right) L_s
\]

\[K_R = \frac{R_s + L_m^2}{L_r^2} R_r / L_r^2\]

(3) \( T = \) Sampling time, \( T_R = \) Rotor time constant = \( L_r / R_r \).

\[A_d = \begin{bmatrix}
1 & \frac{-T m R_r}{L_r K_L} & \frac{-T m \omega_r}{L_r K_L} & 0 & 0 \\
0 & 1 & \frac{-T m R_r}{L_r K_L} & \frac{-T m \omega_r}{L_r K_L} & 0 \\
0 & T m R_r & 1 & \frac{-T} {T_r} \omega_r & 0 \\
0 & 0 & 0 & T \omega_r & 1 - \frac{T} {T_r} \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

(5)

\[B_d = \begin{bmatrix}
1 \\
0 \\
0 \\
0
\end{bmatrix}, \quad C_d = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\]

(6) \( (7) \)

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. 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.
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.
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]:

\[ f = b_{f,i} \sigma(k-t) \]  

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, \( \sigma(k-t) \) 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:

\[ \sigma(k-t) = 0 \text{ if } k < t \text{ and } 1 \text{ if } k > t \]  

If a bias of magnitude \( b_{u,i} \) occurs at time \( t \), in the \( i \)th sensor, the output is given by,

\[ Z(k) = H_{X}(k) + v(k) + b_{u,i} \sigma(k-t) \]  

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

\[ u(k) = m(k) + b_{u,i} e_{u,i} \sigma(k-t) \]  

E. Fault detection and Fault confirmation test

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

\[ \varepsilon(k) = \gamma^T(k)V^{-1}(k)\gamma(k) \]  

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

\[ CP(k/k-1)C^T + R \]  

The test statistic \( \varepsilon(k) \) follows a central Chi-square distribution with \( \alpha \) degrees of freedom. For any level of significance \( \alpha \), 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.

\[ \varepsilon(N,t) = \sum_{k=t}^{t+N} \gamma^T(k)V^{-1}(k)\gamma(k) \]  

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

\[ V_{ds} : \text{d-axis stator applied voltage} \]
\[ V_{qs} : \text{q-axis stator applied voltage} \]
\[ I_{ds} : \text{d-axis stator current in stationary ref. frame} \]
\[ I_{qs} : \text{q-axis stator current in stationary ref. frame} \]
\[ \gamma_\phi : \text{q-axis rotor flux in stationary ref. frame} \]
\[ n_r : \text{Rotor speed} \]
\[ L_m : \text{Mutual inductance} \]
\[ L_s : \text{Stator self inductance} \]
\[ T_r : \text{Rotor time constant} \]

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

REFERENCES


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