Diagnostics Relevant Modeling of Squirrel-Cage Induction Motor: Electrical Faults

SSSR Sarathbabu Duvvuri[1][0000-0001-9653-2519]

[1] Indian Institute of Technology Hyderabad, Kandi TS 534202, INDIA
ee11p1007@iith.ac.in

Abstract. In this paper, simplified SCIM models are formulated based on stationary, rotor and synchronous reference frames. All these models are compared and analyzed in terms of their diagnostic relevance to major electrical faults (stator inter-turn short-circuit and broken rotor bars). Ability to develop distinct residual signatures is a key for any model-based fault diagnosis method. Performance of various models in term of their ability to generate distinct residual and best suited model is recommended based on discriminatory ability index proposed in this manuscript. Extended Kalman filter is most commonly used estimator for nonlinear systems. The SCIM, being a nonlinear system, continuous-time extended Kalman filter is considered for state estimation. As an extesion, parameter sensitivity analysis is carried out for the best suited model. Efforts are made to convey which parameters have a significant effect in case there is plant-model mismatch. Analytical computations are carried out for a 3 kW SCIM motor using MATLAB software. The results show that most effective squirrel-cage induction motor model for model-based fault diagnostics.

Keywords: Continuous-time extended Kalman filter (CTEKF), reference frame theory, squirrel-cage induction motor (SCIM).

1 Introduction

It is well known that condition monitoring and fault diagnosis play a vital role in overall economy of any process or industry. Therefore significant amount of research is carried out in the area of fault diagnosis. While earlier, ease of computation carried significant emphasis, nowadays relatively computationally demanding methodologies, such as observer-based method, are gaining popularity [1]-[8] among academic researchers as well as industry. Primary reason for this change is increased speeds as well as multi-core architecture of processor. With such increased processing capabilities, one can perform fault detection and diagnosis (FDD) using observer-based methods, which bring in additional advantages: (i) quick detection and reliable diagnosis (ii) isolability (iii) robustness and (iv) fault localization [8]-[11].
Observer-based methods rely on residuals or innovations, which are defined as the difference between measured and estimated quantities, to perform the diagnostic task. For an observer-based method to be effective, the innovations should be sensitive to faults and robust to load and/or set point variations [8]. The sensitivity of the innova-

tions may vary with the chosen model. For effective diagnosis, the model should be simple yet accurate as well as computationally efficient. Model-based diagnosis is becoming more and more popular in the area of electrical machine fault diagnosis as well [8]. A large number of models, ranging from very detailed finite element based models to simple models such as models based on reference frame theory are available and proposed. However, as stated earlier, the task of FDD requires computationally non-expensive yet accurate model. As models based on finite element [16], multiple-coupled circuit [17]-[19], and magnetic equivalent circuit [20] are complex and simulating these models in real time is computationally intensive, these models will not be effective for the purpose of FDD. Therefore simpler models based on reference frame theory proposed in [21]-[27], are better suited for machine fault diagnosis. SCIM models can be formulated in stationary, rotor, synchronous and arbitrary reference frames. Similarly, there are different physical variables, which may be chosen as a state variable for an SCIM model. As will be shown later, there are multiple ways in which a physical variable form of an extended state-space model for SCIM can be modeled. This poses some unique questions pertinent to SCIM fault diagnosis.

- Are all the SCIM models are similar?
- Which reference one should prefer for fault diagnostics?
- Which SCIM is diagnostically most relevant?
- Which parameter is highly sensitive in the chosen model in case of plant-model mismatch?

The aim of this paper is to answer all these questions and find the model that is most relevant for SCIM electrical fault diagnosis. Electrical faults i.e. stator inter-turn short-circuit and broken rotor bars, account for nearly 45-50% of total faults in SCIM [1], and thus constitute majority of the faults in SCIM. Since, extended Kalman filter is extensively used nonlinear observer, the same is considered for state estimation of SCIM [1]-[35]. A detailed performance evaluation was carried out to analyze performance of various SCIM models and select the most appropriate model that can generate distinctive residuals and thus are better suited to discriminate. Further, once a model is chosen, the next task is to identify key parameters for the same. Towards this end, a parameter sensitivity analysis is carried out and robustness of an SCIM model to plant-model mismatch is analyzed. It is expected that such detailed analysis will provide a benchmark inappropriate model selection as well as parameter identification for an SCIM model.

The paper is presented as follows: new developed extended SCIM models are presented in detail in Section 2 followed by continuous time extended Kalman filter design and a performance index is defined to compare performance in section 3. Main simulation results and corresponding discussions are presented in Section 4, the manuscript is finalized by concluding remark in Section 5.

2 Extended State-Space Model of SCIM

In this section, an extended SCIM model in physical variable form is formulated. For the development of SCIM Models assumptions presented in - is considered for further analysis. Changes in the inductance are neglected when rotor bar breaks -. 6) The rotor bars are electrically insulated. 7) The effect of friction is neglected as the friction coefficient is imperceptible $\left(B_l \cong 0\right)$. The dynamic equations in machine variables is presented in - as follows.

$$\begin{aligned}
\dot{\boldsymbol{\lambda}}^s_{abc} &= \mathbf{v}^s_{abc} - \mathbf{R}^s_{abc}\mathbf{i}^s_{abc} \\
\dot{\boldsymbol{\lambda}}^r_{abc} &= - \mathbf{R}^r_{abc}\mathbf{i}^r_{abc} \\
\dot{\omega}_r &= \frac{1}{J}\left(T_{em} - T_l\right) \\
\dot{T}_l &= 0
\end{aligned} \tag{1}$$

where, $\mathbf{v}^s_{abc}$ is input to the SCIM in vector notation. Similarly, $\mathbf{i}^s_{abc}$ and $\mathbf{i}^r_{abc}$ are stator currents and rotor currents, respectively. The rotor angular velocity, electromagnetic torque and load torque are denoted by ω_r, T_{em} and T_l, respectively.

In the vector-matrix notation, the stator and rotor flux linkages, stator and rotor currents, winding inductances are related as follows:

$$\begin{bmatrix} \boldsymbol{\lambda}^s_{abc} \\ \boldsymbol{\lambda}^r_{abc} \end{bmatrix} = \begin{bmatrix} \mathbf{L}^s_{abc} & \mathbf{L}^{sr}_{abc} \\ \mathbf{L}^{rs}_{abc} & \mathbf{L}^r_{abc} \end{bmatrix} \begin{bmatrix} \mathbf{i}^s_{abc} \\ \mathbf{i}^r_{abc} \end{bmatrix} \tag{2}$$

The 8th order SCIM model presented in, is computationally intensive. Therefore, the model presented in is transformed using reference frame theory, , as follows:

$$\begin{aligned}
\dot{\boldsymbol{\lambda}}^s_{qd0} &= \mathbf{v}^s_{qd0} - \mathbf{K}_s\mathbf{R}^s_{qd0}\mathbf{K}_s^{-1}\mathbf{i}^s_{qd0} - \omega\mathbf{K}_\omega\boldsymbol{\lambda}^s_{qd0} \\
\dot{\boldsymbol{\lambda}}^r_{qd0} &= - \mathbf{K}_r\mathbf{R}^r_{qd0}\mathbf{K}_r^{-1}\mathbf{i}^r_{qd0} - \left(\omega - n_p\omega_r\right)\mathbf{K}_\omega\boldsymbol{\lambda}^r_{qd0} \\
\dot{\omega}_r &= \frac{1}{J}\left(\frac{3}{2}n_p\,\frac{L_m}{\left(L_sL_r - L_m^2\right)}\left(\lambda^s_q\lambda^r_d - \lambda^s_d\lambda^r_q\right) - T_l\right) \\
\dot{T}_l &= 0
\end{aligned} \tag{3}$$

where, is the transformation angular velocity and is the number of pole pairs. Computational complexity of the model given in (3) is significantly lower compared to the model in reference frame. Similarly, by applying transformation to (2), the corresponding flux linkage equations in reference frame can be formulated as follows:

$$\begin{bmatrix} \boldsymbol{\lambda}^s_{qd0} \\ \boldsymbol{\lambda}^r_{qd0} \end{bmatrix} = \begin{bmatrix} \mathbf{K}_s\mathbf{L}^s_{abc}\mathbf{K}_s^{-1} & \mathbf{K}_s\mathbf{L}^{sr}_{abc}\mathbf{K}_r^{-1} \\ \mathbf{K}_r\mathbf{L}^{rs}_{abc}\mathbf{K}_s^{-1} & \mathbf{K}_r\mathbf{L}^r_{abc}\mathbf{K}_r^{-1} \end{bmatrix} \begin{bmatrix} \mathbf{i}^s_{qd0} \\ \mathbf{i}^r_{qd0} \end{bmatrix} = \begin{bmatrix} \mathbf{L}^s_{qd0} & \mathbf{L}^{sr}_{qd0} \\ \mathbf{L}^{rs}_{qd0} & \mathbf{L}^r_{qd0} \end{bmatrix} \begin{bmatrix} \mathbf{i}^s_{qd0} \\ \mathbf{i}^r_{qd0} \end{bmatrix} \tag{4}$$

Further, stator and rotor currents can be written in terms of flux linkages by inverting

$$\begin{bmatrix} \mathbf{i}^s_{qd0} \\ \mathbf{i}^r_{qd0} \end{bmatrix} = \begin{bmatrix} \mathbf{M}^s_{qd0} & \mathbf{M}^{sr}_{qd0} \\ \mathbf{M}^{rs}_{qd0} & \mathbf{M}^r_{qd0} \end{bmatrix} \begin{bmatrix} \boldsymbol{\lambda}^s_{qd0} \\ \boldsymbol{\lambda}^r_{qd0} \end{bmatrix} \tag{5}$$

The 8th order SCIM model given in can be represented in various physical variable forms, i.e. there are many physical variables, which can be chosen as states. One can select either currents or fluxes on either rotor side or stator side of the machine. Thus, there are four sets of variables available to model the SCIM: i) three stator currents $\mathbf{i}^s_{qd0}$; ii) three rotor currents $\mathbf{i}^r_{qd0}$; iii) three stator fluxes $\boldsymbol{\lambda}^s_{qd0}$ and iv) three rotor fluxes

λ_{qd0}^{r} . One can select any two from above set of variables, which gives rise to $^{4}C_{2}$, i.e. six possible combinations. All the six models are derived systematically presented in the following subsection.

2.1 SCIM models

- ***Model a*: Stator fluxes and rotor fluxes**
- ***Model b*: Stator fluxes and rotor currents**
- ***Model c*: Stator currents and stator fluxes**
- ***Model e*: Stator currents and rotor fluxes**
- ***Model f*: Rotor fluxes and rotor currents**

As stated earlier, the SCIM models presented in can also be written in one of the three reference frames, i.e. stationary, synchronous or rotor reference frame.

It is important to note that ***Model f*** is not feasible for the considered measurements and therefore the same is not discussed further.

Thus one can get fifteen different models for SCIM, i.e. ***Model a, b, c, d, e*** in either stationary, synchronous or rotor reference frames. In order to determine which of these models are suitable for the purpose of FDD of SCIM, a comparative study of the discriminatory ability of residues generated from these models must be carried out. For the model to be diagnostic relevant, the residues must be sensitive to faults and robust to disturbances and load changes.

2.2 Key Parameters for SCIM models

The SCIM models derived in the previous subsection require seven parameters: i) stator phase resistance ii) rotor phase resistance iii) stator leakage inductance iv) rotor leakage inductance v) magnetizing inductance vi) magnetizing inductance and vii) moment of inertia. As the models are nonlinear, effect of parameter variation or plant-model mismatch on diagnostic performance may be different for different parameters. Therefore, the sensitivity of the SCIM model parameters to inaccuracy or changes in parameters is investigated. The influence of different parameters on the residues generated from the model is evaluated in this manuscript.

3 Squirrel-Cage Induction Motor State Estimation Using Continuous-Time Extended Kalman Filter and Discriminatory Ability Index for Model-Based Fault Diagnosis

The state estimates for SRIM is obtained from continuous-time extended Kalman filter (CTEKF),. The residual or innovations are generated as follows:

$$\boldsymbol{\gamma}(k)=\mathbf{y}(k)-\mathbf{C}(k)\hat{\mathbf{x}}(k\,|\,k-1) \tag{6}$$

Under normal operating conditions, innovations or residuals presented in follow Gaussian distribution. However, when a rotor inter-turn fault occurs, these innovations become non-white. Here, out of the fifteen various models for SRIM, which model(s) is(are) diagnostically relevant has to be determined. For finding suitable model, a new discriminatory ability index (DAI) based on residual (innovations) sum of squares (RSS, denoted by Γ) is proposed in

$$\begin{aligned}
&\Gamma = \sum_{k=t}^{t+N} \boldsymbol{\gamma}(k)^{\mathrm{T}} \boldsymbol{\gamma}(k) \\
&\bar{\Gamma} = \sum_{i} \frac{\Gamma(i)}{m} \\
&\mathrm{DA} = \begin{cases} \dfrac{\Gamma_f - \bar{\Gamma}}{\bar{\Gamma}} \times 100 & \Gamma_f > \Gamma_{\max} \\ 0 & \Gamma_f < \Gamma_{\max} \end{cases}
\end{aligned} \tag{7}$$

where, $\Gamma_{\max}$ denotes empirically obtained maximum value of Γ during normal operation. A proposed discriminatory ability index can be used to compare relative performance of various models.

4 Main Simulation Results and Observations

Simulations were carried out for fifteen different state space models of SCIM. The SCIM is fed from an unbalanced three-phase supply, state estimation is carried out using standard extended Kalman filter. Diagnostic ability index is calculated for the proposed different induction motor models is presented in this section.

4.1 Stator inter-turn fault and rotor inter-turn fault

In this simulation study, covariance matrices are considered in diagonal form for state estimation and the sampling time is $T = 0.1ms$. The performance of various models was computed with one percent stator inter-turn short-circuit and one broken rotor bar fault severity. In simulations, a stator inter-turn fault presented in is introduced at $t = 0.2$ second. The fault can be detected if the innovations deviate from zero mean Gaussian white noise sequence. The proposed DA index was calculated for all the models and has been tabulated in Table II. A higher value of DA index indicates larger deviation from a Gaussian distribution and that a fault can be detected easily by a residual based diagnosis method.

As can be seen from the Table II, not all models show same amount of discriminatory ability towards stator fault. The models best suited for stator fault diagnosis are:

- SCIM model with state variables as $\left(\mathbf{i}^{s}_{qd0},\ \mathbf{i}^{r}_{qd0},\ \omega_r,\ T_l\right)$, i.e. ***Model d*** in the stationary reference frame.
- SCIM model with state variables as $\left(\mathbf{i}^{s}_{qd0},\ \boldsymbol{\lambda}^{s}_{qd0},\ \omega_r,\ T_l\right)$, i.e. ***Model c*** in the stationary reference frame.

The results are also validated by observing the autocorrelation coefficients as shown in Fig. 1 and Fig. 2. As can be seen from the figure, when ***Model d*** in the stationary reference frame is used for CTEKF, residues become non-Gaussian. The same is also validated by the autocorrelation coefficients, which suggest that the residues have become non-Gaussian after introduction of a stator fault and rotor fault.

Table-I

SCIM PARAMETERS USED IN SIMULATIONS

Parameter	**Variable**	**Value**
Rated power	P_{rated}	3 kW
Rated stator voltage	V_l	380 V
Rated speed	N_r	1430 rpm
Rated stator frequency	f_s	50 Hz
Number of stator turns	N_s	312
Number of rotor bars	N_b	28
Stator phase resistance	r_s	2.283 Ω
Rotor phase resistance	r_r	2.133 Ω
Magnetizing inductance	L_{ms}	146.7 *m*H
Magnetizing inductance	L_{mr}	146.7 *m*H
Stator leakage inductance	L_{ls}	11.1 *m*H
Rotor leakage inductance	L_{lr}	11.1 *m*H
Moment of inertia	J	0.06 kg.m^2

Table-II

Performance Index for Different SCIM Models

Model	**State Variables**	**Reference Frame**	**DA**	
			Stator Inter-turn	**Broken Rotor Bars**
a	Stator fluxes and rotor fluxes	Stationary	0	60.08
		Synchronous	11.0628	43.82
		Rotor	0	53.84
b	Stator fluxes and rotor currents	Stationary	0	33.54
		Synchronous	0	0
		Rotor	0	0
c	Stator currents and stator fluxes	Stationary	101.185	0
		Synchronous	0	0
		Rotor	0	0
d	**Stator currents and rotor currents**	**Stationary**	**105.61**	**111.71**
		Synchronous	27.0767	0
		Rotor	0	0
e	Stator currents and rotor fluxes	Stationary	82.2875	0
		Synchronous	0	0
		Rotor	0	0

4.2 Robustness to Parameter variations

As ***Model d*** in the stationary reference frame is the most suitable model for fault diagnosis, only that model is considered for further analysis. Any system may undergo degradation of performance over time. This degradation would mean parameter of the system may vary. Therefore it is important to analyze sensitivity of residues to parameter variation or plant-model mismatch. Each of the seven key parameters was varied and simulations were carried out. Similar to the previous subsection, the best suited SCIM model is fed from a balanced supply, and state estimation is carried out using CTEKF.

In simulations, percentage change in one of the key parameters is introduced at $t = 0.2$ second. The change in parameter will lead to plant-model mismatch, which should deviate residues from zero mean Gaussian white noise sequence. The purpose of the analysis carried out in this subsection is to identify the percentage range of the key parameters such that plant-model mismatch is not detected as a fault. The limits for inaccuracies of the parameters in terms of percentages are presented in Table III. If the mismatch between the actual motor and the model parameters is larger than what is indicated in Table III, the innovations will become non-Gaussian, causing a residual based fault diagnosis method to generate false alarms.

As seen from Table III, not all the parameters show same amount of parameter sensitivity. The parameters may be classified into three categories as shown below:

- Highly sensitive parameters: Magnetizing inductances L_{ms} and L_{mr} .
- Moderately sensitive parameters: Stator leakage inductance L_{ls} and stator phase resistance r_s .
- Highly insensitive parameters: Rotor leakage inductance L_{lr} , rotor phase resistance r_r and moment of inertia J .

However, the all the figures are omitted due to brevity.

Table-III

Parameter Sensitivity Index for SCIM Model

Serial No	**Key Parameters**	**Variable**	**Range of model inaccuracies in terms of %**
1	**Magnetizing inductance**	L_{ms}	**± 3%**
2	**Magnetizing inductance**	L_{mr}	**± 3%**
3	*Stator leakage inductance*	L_{ls}	***± 10%***
4	*Stator phase resistance*	r_s	***± 30%***
5	Rotor phase resistance	r_r	± 60%
6	Rotor leakage inductance	L_{lr}	± 80%
7	Moment of inertia	J	± 90%

5 Conclusion

The SCIM models were formulated with various state variables in one of the reference frames. Diagnostic relevance of these SCIM models for major electrical faults was evaluated. It was found that not all SCIM models could generate diagnostically relevant residuals and thus have varying discriminatory capabilities. In order to compare diagnostic relevance of various models, a discriminatory ability index is proposed in this paper. It can be concluded that ***Model d*** in the stationary reference frame is best suited or diagnostically most relevant for model-based FDD. This has also been validated through exhaustive simulation studies.

The parameter sensitivity analysis for the best suited model is done, and acceptable percentage inaccuracies of the model parameters for robust fault diagnosis are provided.

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