Parameter Estimation Using Particle Filter for Induction Machines under Inter-Turn Fault

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ABSTRACT

Parameter estimation has found its applications in various domains. In this paper, it is applied for fault severity estimation. A method, using particle filter approach, for estimating unknown constant fault parameters in stator winding inter-turn short is proposed. These parameters are insulation resistance and percentage of shorted turns. The method uses only measurements of stator voltages and currents. In order to effectively estimate the parameters, firstly, a sequence components-based approach is applied to derive an equality constraint on the magnitude of a state variable, which works as additional information for estimation algorithm based on state-state model. Secondly, the variance reduction technique is applied to increase the accuracy of the method.

1. INTRODUCTION

Induction machines are widely used in modern industries due to its rugged construction. They are subject to faults due to aging, severe operating conditions, and harsh environments. These faults can be categorized into different groups, including stator-related fault, rotor electrical fault, rotor mechanical fault, and power electronic component fault in the drive system (Henao et al., 2014). From amongst this list, the winding inter-turn short is seen to be a common fault, which can cause catastrophic damage to the electrical machines and the associated systems. Once this fault has occurred, it can result in severe faults such as phase-to-phase, phase-to-ground faults (Arkan et al., 2001). This fact highlights the importance of the diagnosis of this fault.

Condition-based maintenance requires the diagnosis process to not only detect fault, but also evaluate the severity of the fault condition. In addition, the development of advanced condition-based monitoring requires the incorporation of the degradation prediction and remaining useful life (RUL) estimation into an integrated health monitoring system. The estimation of severity information becomes the enabler for this development. Even though the fault detection for stator winding inter-turn fault has been matured, the techniques for its severity estimation remain limited. While various quantities have been proposed to detect the fault, such as those based on stator currents (Seshadrinath et al., 2014, De Angelo et al., 2009, Tallam et al., 2002), fluxes (Henao et al., 2003, Lamim Filho et al., 2014), vibration signals (Lamim Filho et al., 2014, Jin et al., 2015), their applications to severity estimation are limited. Firstly, it lacks a physical link between these quantities and the fault. Secondly, due to the influence of voltage imbalance, load variation, and inherent asymmetry, these quantities may not represent monotonic trend when fault progresses. The fault parameters, which are the insulation resistance and fraction of shorted turns, are closely related to the degradation process, and hence the estimation of these parameters is considered in this paper. Since fault develops and progresses slowly, fault parameters can be considered as constant for each fault severity level. The severity estimation, therefore, becomes the problem of estimating constant parameters. The fraction of shorted turns is estimated using observer and parameter estimation techniques, as proposed in (Kallesoe et al., 2004) and (Bachir et al., 2006), respectively. In (Angelo et al., 2009), a severity factor is proposed for assessing fault condition using sequence component analysis. It is considered as an indicator combining the effects of both fault parameters. However, they are tested for only small values of fault loop resistance. In (Nguyen et al., 2015), a closed-form solution for fault parameters based on the steady-state analysis of a faulty machine is proposed, but the estimation accuracy can be influenced by the inherent imbalance of voltage supplies. Also, since the closed-form expression depends on angle information, it can be sensitive to measurement errors. In (Nguyen et al., 2016), an approximate equality constraint on fault parameters has been applied to simplify the state-space model, so that only one unknown parameter is estimated, and the other parameter is determined using the constraint. In this paper, an equality constraint, the magnitude of a state variable in state-space model, is directly used as prior information for the parameter estimation process. Both unknown parameters are estimated simultaneously and no measurements, other than voltages and currents, are required.

Particle filter (PF) has been proven to be a suitable technique for parameter estimation (Orchard and Vachtsevanos, 2009, Zio and Peloni, 2011). It can be applied to nonlinear systems of non-Gaussian noise since it does not require analytical forms of probability density function (pdf). Also, considering parameter estimation for modeling and prediction of the degradation process, there is a set of different particles of which each will propagate on their own trajectories. The significant convenience of the PF based approach lies on its statistical nature, in which the set of trajectories can be employed to manage the uncertainty of data modeling and RUL estimation results. PF will be applied to show the feasibility of PF-based approach for parameter estimation, which is used directly for severity estimation in this work, and can be applied for degradation process modeling and RUL estimation, if required.

The contribution of the paper is threefold. The first is the PF approach to fault parameter estimation of an induction machine under inter-turn fault. The second is the derivation of an equality constraint on a state variable in state-space model, which helps reduce the range of the parameter domain. Thirdly, the paper demonstrates the variance reduction technique for estimating constant parameters. For the filter-based approach, a constant parameter is modeled as a random process in which the value in the next time step is the sum of the current value and a random noise. The value of this variance will have effect on the convergence rate and range of the estimated parameters. In this paper, the variance is reduced over time in the estimation duration to improve its convergence and accuracy. The paper is organized as below. Section 2 presents the qd model and state-space model of a machine under fault. Section 3 discusses the PF approach. Section 4 derives the equality constraint based on the sequence component model of the faulty machine. Section 5 presents the estimation method using the equality constraint. Section 6 provides simulation results and discussions, and Section 7 concludes the paper.

2. ANALYTICAL MODEL OF AN INDUCTION MACHINE UNDER STATOR WINDING INTER-TURN FAULT

2.1. Description of Stator Winding Inter-Turn Short Circuit Fault and Fault Parameters.

Fig. 1 shows the stator winding of a star-connected three-phase induction machine under inter-turn fault in phase a. The fault is represented by two parameters, the fraction of shorted turns μ, and fault loop resistance r_f, described as

$$\mu = \frac{N_{as_f}}{N_{as}} \tag{1}$$

where N_{as_f} and N_{as} are the number of turns in the faulty portion as_f and the total winding as of the faulty phase winding, respectively, and rf is the insulation resistance of the stator winding fault loop portion.

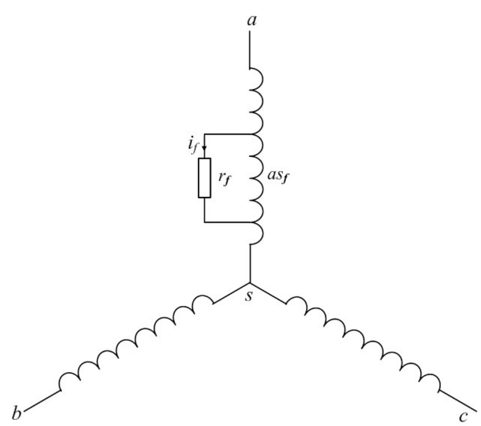

Figure 1. Stator winding under inter-turn short circuit fault in phase a.

2.2. qd Model of an Induction Machine under Stator Winding Inter-Turn Short Circuit Fault

In this section, the model of a faulty machine under fault occurring in phase a is described. The set of equations describing the faulty machine is as follows (Tallam et al., 2002, Nguyen et al., 2015).

$$\boldsymbol{v}_{qds} = R_s \boldsymbol{i}_{qds} + \frac{d\boldsymbol{\lambda}_{qds}}{dt} - \mu R_s i_f [2/3 \quad 0]^T \tag{2}$$

$$\boldsymbol{0} = R_r \boldsymbol{i}_{qdr} + \frac{d\boldsymbol{\lambda}_{qdr}}{dt} + \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \boldsymbol{\lambda}_{qdr} \tag{3}$$

$$\boldsymbol{\lambda}_{qds} = \boldsymbol{L}_s \boldsymbol{i}_{qds} + \boldsymbol{L}_m \boldsymbol{i}_{qdr} - \mu L_s i_f [2/3 \quad 0]^T \tag{4}$$

$$\boldsymbol{\lambda}_{qdr} = \boldsymbol{L}_m \boldsymbol{i}_{qds} + \boldsymbol{L}_r \boldsymbol{i}_{qdr} - \mu L_m i_f [2/3 \quad 0]^T \tag{5}$$

$$r_f i_f = \mu R_s (i_{qs} - i_f) + \frac{d\lambda_f}{dt} \tag{6}$$

$$\lambda_f = \mu (L_s i_{qs} + L_m i_{qr}) - \mu i_f \left(L_{ls} + \frac{2}{3} \mu L_m \right) \tag{7}$$

$$T_e = \frac{3P}{4} L_m\left(i_{qs} i_{dr} - i_{ds} i_{qr}\right) - \frac{P}{2}\mu L_m i_f i_{dr} \tag{8}$$

$$\frac{d\omega_r}{dt} = \frac{P}{2J}(T_e - T_L - B\omega_r) \tag{9}$$

In the equations above, $\boldsymbol{v}_{qds} = [v_{qs} \quad v_{ds}]^T, \boldsymbol{i}_{qds} = [i_{qs} \quad i_{ds}]^T$, $\boldsymbol{\lambda}_{qds} = [\lambda_{qs} \quad \lambda_{ds}]^T$, $\boldsymbol{i}_{qdr} = [i_{qr} \quad i_{dr}]^T$, $\boldsymbol{\lambda}_{qdr} = [\lambda_{qr} \quad \lambda_{dr}]^T$. v_{qs}, v_{ds} are the q–axis and d–axis components of stator voltages. $\lambda_{qs}, \lambda_{ds}$ are the q–axis and d–axis components of stator flux linkages. $\lambda_{qr}, \lambda_{dr}$ are the q–axis and d–axis components of rotor flux linkages. i_{qs}, i_{ds} are the q–axis and d–axis components of stator currents. i_{qr}, i_{dr} are the q–axis and d–axis components of rotor currents. λ_f is the flux linkage of the faulty winding portion. i_f is the fault loop current. R_s, R_r are the stator resistance and rotor resistance. L_s, L_{ls}, L_r, L_m are the stator inductance, stator leakage inductance, rotor inductance, and magnetizing inductance. T_e is the electromagnetic torque. T_L is the load torque. ω_r is the rotor speed. P is the number of poles. J is the rotor inertia, and B is the friction coefficient.

2.3. State-Space Model of an Induction Machine under Stator Winding Inter-Turn Short Circuit Fault

In order to estimate fault parameters, the state-space model is augmented to incorporate the parameters as the new variables. Define $z_1 = i_{qs}, z_2 = i_{ds}, z_3 = -i_{qs} + \frac{a}{c}\lambda_{qs}$, $z_4 = -i_{ds} + \frac{a}{c}\lambda_{ds}$, $z_5 = \frac{1}{3}\mu i_f, z_6 = r_f, z_7 = \mu, z_8 = \omega_r$, and state vector $\boldsymbol{z} = [z_1\ z_2\ z_3\ z_4\ z_5\ z_6\ z_7\ z_8]^T$, input vector $\boldsymbol{u} = [v_{qs}\ v_{ds}\ T_L]^T$, and output vector $\boldsymbol{y} = \left[i_{qs}\ i_{ds}\right]^T$, the corresponding state equations are

$$\frac{d\boldsymbol{z}}{dt} = \left(A_z + \omega_r A_{\omega_r}\right)\boldsymbol{z} + B_z + B_{1z}\boldsymbol{u} + B_2\boldsymbol{u} \tag{10}$$

$$\boldsymbol{y} = C_z \boldsymbol{z} \tag{11}$$

where

$$A_z = \begin{bmatrix} A\boldsymbol{I}_{2\times2} & \frac{bc}{a}\boldsymbol{I}_{2\times2} & \begin{bmatrix} -2a - \frac{2R_s}{L_{ls}} - \frac{2z_6}{z_7(1-2z_7/3)L_{ls}} \\ 0 \end{bmatrix} & \boldsymbol{0}_{2\times3} \\ B\boldsymbol{I}_{2\times2} & B\boldsymbol{I}_{2\times2} & \begin{bmatrix} \frac{2R_s}{L_{ls}} + \frac{2z_6}{z_7(1-2z_7/3)L_{ls}} \\ 0 \end{bmatrix} & \boldsymbol{0}_{2\times3} \\ \boldsymbol{0}_{1\times2} & \boldsymbol{0}_{1\times2} & \frac{R_s}{L_{ls}} - \frac{z_6}{z_7(1-2z_7/3)L_{ls}} & \boldsymbol{0}_{1\times3} \\ \boldsymbol{0}_{2\times2} & \boldsymbol{0}_{2\times2} & \boldsymbol{0}_{2\times1} & \boldsymbol{0}_{2\times3} \\ \boldsymbol{0}_{1\times2} & \boldsymbol{0}_{1\times2} & 0 & \begin{bmatrix} 0 & 0 & -\frac{BP}{2J} \end{bmatrix} \end{bmatrix} \tag{12}$$

$$A_{\omega_r} = \begin{bmatrix} \frac{ce}{a}\boldsymbol{J} & \frac{ce}{a}\boldsymbol{J} & \boldsymbol{0}_{2\times4} \\ -\left(1+\frac{ce}{a}\right)\boldsymbol{J} & -\left(1+\frac{ce}{a}\right)\boldsymbol{J} & \boldsymbol{0}_{2\times4} \\ \boldsymbol{0}_{4\times2} & \boldsymbol{0}_{4\times2} & \boldsymbol{0}_{4\times4} \end{bmatrix} \tag{13}$$

$$B_z = \begin{bmatrix} 0_{7\times1} \\ \frac{3cL_mP^2}{8aL_rJ}(z_1z_4 - z_2z_3 - z_2z_5 - z_4z_5) \end{bmatrix} \tag{14}$$

$$B_{1z} = \begin{bmatrix} \frac{2z_7}{3(1-2z_7/3)L_{ls}} & \boldsymbol{0}_{1\times2} \\ 0 & \boldsymbol{0}_{1\times2} \\ -\frac{2z_7}{3(1-2z_7/3)L_{ls}} & \boldsymbol{0}_{1\times2} \\ 0 & \boldsymbol{0}_{1\times2} \\ \frac{z_7}{3(1-2z_7/3)L_{ls}} & \boldsymbol{0}_{1\times2} \\ \boldsymbol{0}_{3\times1} & \boldsymbol{0}_{3\times2} \end{bmatrix} \tag{15}$$

$$B_2 = \begin{bmatrix} g\boldsymbol{I}_{2\times2} & \boldsymbol{0}_{2\times1} \\ -g\boldsymbol{I}_{2\times2} & \boldsymbol{0}_{2\times1} \\ \boldsymbol{0}_{3\times2} & \boldsymbol{0}_{3\times1} \\ \boldsymbol{0}_{1\times2} & -\frac{P}{2J} \end{bmatrix} \tag{16}$$

$$C_z = [\boldsymbol{I}_{2\times2} \quad \boldsymbol{0}_{2\times6}] \tag{17}$$

$\boldsymbol{I}_{n\times n}$ is the n-by-n identify matrix, $\boldsymbol{0}_{n\times m}$ is the n-by-m zero matrix. $\boldsymbol{J} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$, $a = \left(-\frac{R_r L_m^2}{L_r \nabla} - \frac{R_s L_r}{\nabla}\right)$, $c = \frac{R_r L_m}{L_r}$, $b = \frac{R_r L_m}{L_r \nabla}$, $d = -\frac{R_r}{L_r}$, $e = \frac{L_m}{\nabla}$, $g = \frac{L_r}{\nabla}$, $A = \left(a + \frac{bc}{a}\right)$, $B = \left(d - \frac{bc}{a}\right)$, and $\nabla = L_s L_r - L_m^2$.

3. PARAMETER ESTIMATION USING PARTICLE FILTER

PF is a generic technique for parameter estimation. It is a sequential Monte Carlo technique that has been proven as an effective technique for various prognosis problems (Orchard and Vachtsevanos, 2009, Zio and Peloni, 2011). It can be applied to nonlinear systems of both Gaussian and non-Gaussian noise since it does not require analytical forms of pdf. Instead, it approximates pdf by using a set of particles and the associated weights (Arulampalam et al., 2002). Moreover, compared to other estimation methods applicable to nonlinear systems, such as extend Kalman filter, it does not require linearization using Jacobian matrix.

PF is a nonlinear Bayesian filter which recursively estimates posterior pdf through two steps, the prediction step to estimate the prior pdf, and the update step to estimate the posterior pdf using the current measurements. A pdf is represented by a set of random particles along with associated weights.

$$p\left(\boldsymbol{z}(k)\middle|\boldsymbol{y}(1{:}k)\right) \approx \sum_{i=1}^{N} w^{(i)}(k)\, \delta(\boldsymbol{z}(k) - \boldsymbol{z}^{(i)}(k)) \tag{18}$$

where $\boldsymbol{z}(k)$ means the value of $\boldsymbol{z}$ at instant k, $\boldsymbol{z}^{(i)}(k), i = 1{:}N$, denotes a set of random particles drawn from $p\left(\boldsymbol{z}(k)\middle|\boldsymbol{y}(1{:}k)\right)$, N is the number of particles, $w^{(i)}(k)$ is the weight associated with particle $\boldsymbol{z}^{(i)}(k)$, and $\delta(\cdot)$ is the

Dirac delta function. Hence, the prediction and update steps of a pdf become that of particles and weights in PF approach. The particles and weights are chosen using the principle of importance sampling (Doucet et al., 2000), and hence the corresponding filter is called sequential importance sampling (SIS) particle filter. A common problem with the SIS particle filter is the degeneracy phenomenon. That is, after few recursions, most of particles converge to negligible weights. Other types of particle filter such as auxiliary sampling importance resampling (Pitt and Shephard, 1999), regularized particle filter (Musso et al., 2001), and sequential importance resampling (SIR) (Gordon et al., 1993) have been proposed to overcome this problem. SIR technique is applied in this paper due to its intuitive and simple implementation. The steps of SIR particle filter are described in Fig. 2.

The discrete state-space model can be derived from the model in Section 2.3 using the Eular method presented (Braun, 1975).

$$\mathbf{z}(k+1) = f(\mathbf{z}(k), \mathbf{u}(k)) + \boldsymbol{v}(k) \tag{19}$$

$$\mathbf{y}(k) = C_z \mathbf{z}(k) + \boldsymbol{\eta}(k) \tag{20}$$

where $\boldsymbol{v}$ and $\boldsymbol{\eta}$ are process and measurement noises with variance matrices Q and R, respectively.

SIR particle filter algorithm

1. Initialize $z^{(i)}(0)$ and associated weights $w^{(i)}(0)$, $i = 1{:}N$, and set $k = 0$.
2. Predict next state variables using the process model

$$z^{(i)}(k+1|k) \sim p\left(z(k+1)|z^{(i)}(k)\right),$$

i.e., $$z^{(i)}(k+1|k) = f\left(z^{(i)}(k|k), u(k)\right) + v^{(i)}(k).$$

3. Calculate likelihood

$$w^{(i)}(k+1) = p\left(y(k)|z^{(i)}(k+1|k)\right).$$

4. Normalize weights

$$w^{(i)}(k+1) = \frac{w^{(i)}(k+1)}{\sum_{i=1}^{N} w^{(i)}(k+1)}.$$

5. Resample

$$index = resampling\left(w^{(i)}(k+1)\right),$$
$$z^{(i)}(k+1|k+1) = z^{(i)}(k+1|k)(index).$$

6. $k = k+1$, and start the iteration process again from Step 2 above.

Figure 2. Sequential steps of SIR particle filter.

4. CONSTRAINT OF A STATE VARIABLE USING SEQUENCE COMPONENT-BASED APPROACH

The equality constraint is derived from the sequence component model of the faulty induction machine. The qd model of a faulty machine can be transformed into the sequence component model (De Angelo et al., 2009) as

$$\tilde{V}_{sp} = (R_s + j\omega_e L_s)\left(\tilde{I}_{sp} - \tfrac{1}{3}\mu\tilde{I}_f\right) + j\omega_e L_m \tilde{I}_{rp} \tag{21}$$

$$\tilde{V}_{sn} = (R_s + j\omega_e L_s)\left(\tilde{I}_{sn} - \frac{1}{3}\mu\tilde{I}_f\right) + j\omega_e L_m \tilde{I}_{rn} \tag{22}$$

$$0 = \left(\frac{R_r}{s} + j\omega_e L_r\right)\tilde{I}_{rp} + j\omega_e L_m\left(\tilde{I}_{sp} - \frac{1}{3}\mu\tilde{I}_f\right) \tag{23}$$

$$0 = \left(\frac{R_r}{2-s} + j\omega_e L_r\right)\tilde{I}_{rn} + j\omega_e L_m\left(\tilde{I}_{sn} - \frac{1}{3}\mu\tilde{I}_f\right) \tag{24}$$

$$\left(R_f + j\omega_e L_f\right)\tilde{I}_f = \mu(\tilde{V}_{sp} + \tilde{V}_{sn}) \tag{25}$$

where $\tilde{V}_{sp}, \tilde{V}_{sn}$ are positive and negative components of stator voltages, respectively. $\tilde{I}_{sp}, \tilde{I}_{sn}$ are positive and negative components of stator currents, respectively. $\tilde{I}_{rp}, \tilde{I}_{rn}$ are positive and negative components of rotor currents, respectively. $\tilde{I}_f$ is fault loop current phasor. ω_e is the excited electrical frequency. s is motor slip. $R_f = \mu\left(1 - \frac{2\mu}{3}\right)R_s + r_f$, and $L_f = \mu\left(1 - \frac{2\mu}{3}\right)L_{ls}$.

From Eq. (22) and Eq. (24), the fault-dependent quantity $\frac{1}{3}\mu\tilde{I}_f$ and can be estimated as

$$\frac{1}{3}\mu\tilde{I}_f = \Delta_n \tag{26}$$

where

$$\Delta_n = \tilde{I}_{sn} - \frac{\tilde{V}_{sn}}{Z_{nn}} \tag{27}$$

$$Z_{nn} = (R_s + j\omega_e L_s) + \frac{\omega_e^2 L_m^2}{\frac{R_r}{2-s} + j\omega_e L_r} \tag{28}$$

For applications in which motors are operated near the rated speed, s is small, and hence $\frac{1}{3}\mu\tilde{I}_f$ can be calculated assuming $(2 - s) \approx 2$. That is, it is independent of slip.

Further analysis on Eq. (25) provides

$$\mu\tilde{I}_f = \frac{\mu^2(\tilde{V}_{sp} + \tilde{V}_{sn})}{\mu\left(1 - \frac{2\mu}{3}\right)R_s + r_f + j\omega_e\mu\left(1 - \frac{2\mu}{3}\right)L_{ls}} \tag{29}$$

It means the magnitude of $\frac{1}{3}\mu\tilde{I}_f$ depends on both parameters μ and r_f. Therefore, magnitude of $\frac{1}{3}\mu\tilde{I}_f$, once estimated, can be used as an equality constraint for the parameter estimation algorithm.

$$|\mu\tilde{I}_f| = \frac{\mu^2\sqrt{\tilde{V}_{sp}^{\;2} + \tilde{V}_{sn}^{\;2}}}{\sqrt{(\mu\left(1 - \frac{2\mu}{3}\right)R_s + r_f)^2 + (j\omega_e\mu\left(1 - \frac{2\mu}{3}\right))^2}} \tag{30}$$

5. A PROPOSED TECHNIQUE TO ESTIMATE FAULT PARAMETERS BASED ON EQUALITY CONSTRAINT

The scheme to estimate fault parameters is proposed in Fig. 3. The algorithm is run until the estimate of z_5, based on the state-space model using the PF approach, is close to its estimated value using the sequence component approach, expressed in Eq. (26).

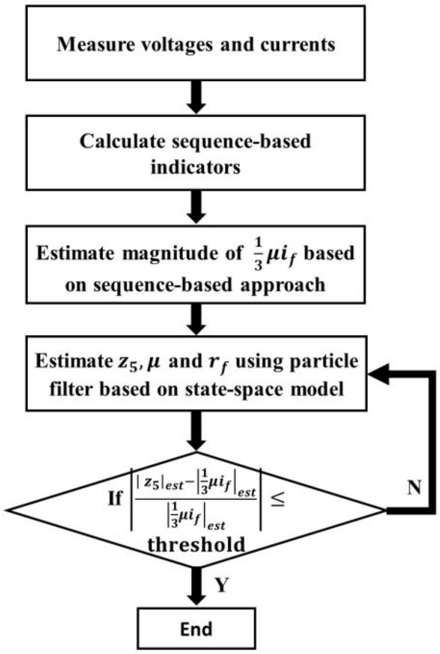

Figure 3. Scheme for estimating μ and r_f.

6. SIMULATION RESULTS

6.1. Simulation Design

The machine used in the simulation is a squirrel cage induction motor of 1.5 kW, 415 V, and 10.2 Nm. The parameters of the motor are shown in Table 1.

Table 1. Parameters of the induction machine used for simulation.

Motor Parameter	Value	Motor Parameter	Value
R_s	7.2050 Ω	L_m	282.0 mH
R_r	6.8255 Ω	J	20.17× 10^{-3} kg.m^2
L_{ls}	13.1 mH	B	4
L_r	282.0 mH	P	10^{-4} Nm.sec
Rated T_L	10.2 Nm	Rated ω_r	1427 rpm
r_f	11.7 Ω	μ	10%

It is assumed that there are noises in the measurements of voltages and currents only. Matrices Q and R can be derived from the simulated Gaussian noise characteristics of measurement devices. MATLAB® and Simulink® software is used in the simulation. The simulation system is organized into three modules. A m-file module generates the stator currents. A Simulink model calculates the sequence components of stator voltages and currents and estimates $\frac{1}{3}\mu\tilde{I}_f$. Another m-file model utilizes the magnitude of $\frac{1}{3}\mu\tilde{I}_f$ as a constraint to estimate μ and r_f using PF approach.

6.2. Validation of Equality Constraint

In order to validate the equality constraint, the estimate of $\frac{1}{3}\mu\tilde{I}_f$ based on Eq. (26) is compared with the simulated values under different fault severity conditions. They are matching, as shown in Fig. 4.

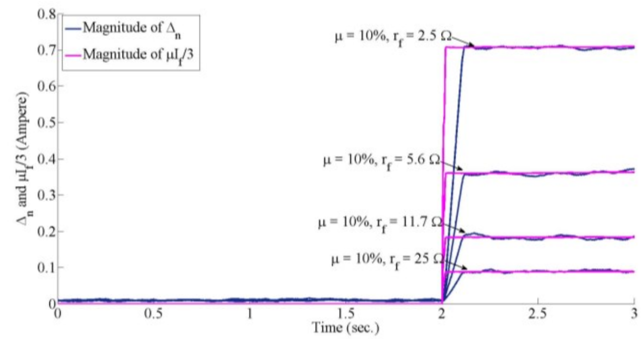

Figure 4. $\frac{1}{3}\mu\tilde{I}_f$ is estimated correctly using Δ_n.

6.3. Estimation of Fault Parameters without Using Variance Reduction Technique

The progression of fault parameters is expressed in the equations below.

$$r_f(k+1) = r_f(k) + q_6(k) \quad (31)$$

$$\mu(k+1) = \mu(k) + q_7(k) \quad (32)$$

where, $q_6 \sim N(0; 10^{-8})$ and $q_7 \sim N(0; 10^{-10})$. The estimate of $\frac{1}{3}\mu\tilde{I}_f$ without using the constraint is shown in Fig. 5. PF algorithm runs at 100 times with $N = 100$. The algorithm can converge to wrong values of $\frac{1}{3}\mu\tilde{I}_f$. The corresponding estimate of μ is shown in Fig. 6. It can take values in large range.

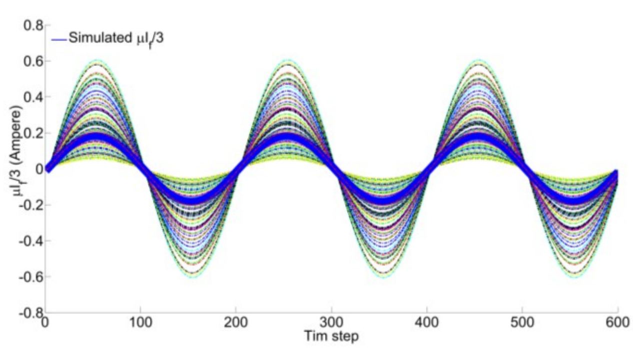

Figure 5. Estimate of $\frac{1}{3}\mu\tilde{I}_f$ without using equality constraint.

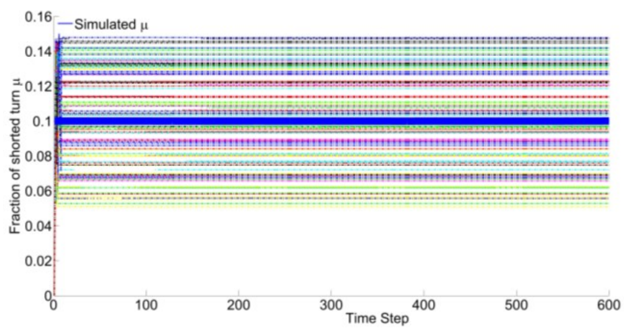

Figure 6. Estimate of μ without using equality constraint.

When the constraint is applied, the estimates of $\frac{1}{3}\mu\tilde{I}_f$ and μ are depicted in Fig. 7 and Fig. 8, respectively. μ is estimated correctly in a small range around the true value. As seen in the figure, the algorithm converges fast to the estimated values but without much adaptation.

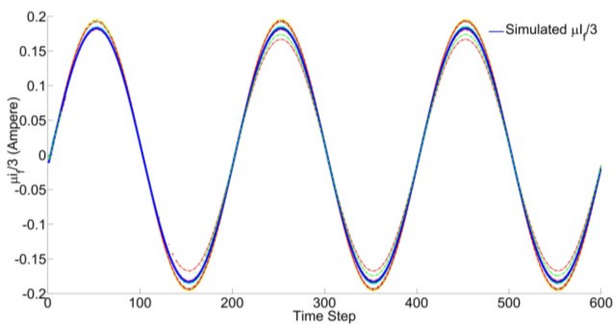

Figure 7. Estimate of $\frac{1}{3}\mu\tilde{I}_f$ using equality constraint.

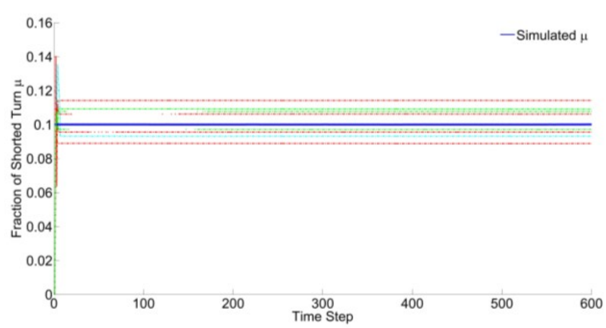

Figure 8. Estimate of μ using equality constraint.

6.4. Estimation of Fault Parameters Using Variance Reduction Technique

In this section, variances of q_6 and q_7 are varied according to $q_6 \sim N(0; 10^{-3} - 4.999 \times 10^{-7} \times k$ and $q_7 \sim N(0; 10^{-5} - 4.999 \times 10^{-9} \times k$. This provides large adjustments at the early stage and ensures the convergence at the later stage. Without using equality constraint, the estimate of $\frac{1}{3}\mu\tilde{I}_f$ is still correct, as shown in Fig. 9. This is the advantage of variance reduction technique. Estimate of μ is depicted in Fig. 10. Equality constraint helps increase the accuracy of the estimation process, as shown in Fig. 11 and Fig. 12 for estimates of μ and r_f , respectively

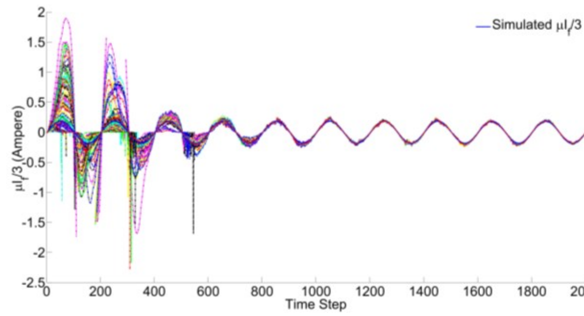

Figure 9. Estimate of $\frac{1}{3}\mu\tilde{I}_f$, using variance reduction, without using equality constraint.

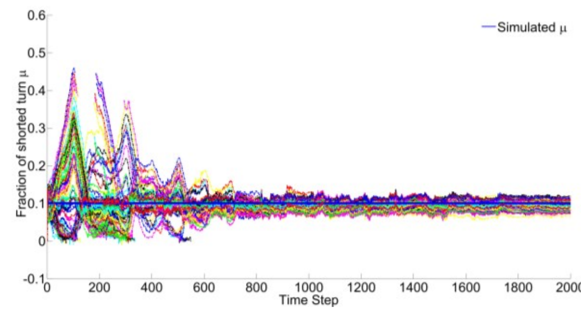

Figure 10. Estimate of μ, using variance reduction, without using equality constraint.

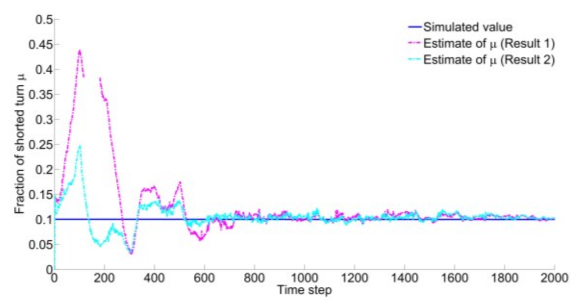

Figure 11. Estimate of μ, using variance reduction and equality constraint.

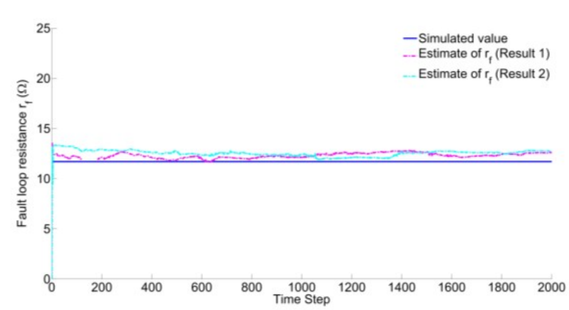

Figure 12. Estimate of r_f, using variance reduction and equality constraint.

7. CONCLUSION

In this work, a parameter estimation method using particle filter is proposed for estimating fault parameters of induction machines under stator winding inter-turn short fault. The estimation results are improved by applying an equality constraint and variance reduction technique. The equality constraint is derived from the sequence component model of the faulty machine. Only measurements of stator voltages and currents In this work, a parameter estimation method using particle filter is proposed for estimating fault parameters of induction machines under stator winding inter-turn short fault. The estimation results are improved by applying an equality constraint and variance reduction technique. The equality constraint is derived from the sequence component model of the faulty machine. Only measurements of stator voltages and currents.

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