Induction Motor Fault Detection Based on Parameter Identification
Using Genetic Algorithm

Juggrapong Treetrong

Abstract
This paper proposes a new scheme of induction motor parameter estimation using Genetic algorithm (GA) for condition monitoring. The flux linkage model and torque model of an induction motor are adapted to the estimation. The scheme is developed to obtain all the motor parameters: stator and rotor resistance, stator and rotor leakage reactance and magnetizing reactance, which paves the way to diagnose different types of the faults. The scheme minimizes the difference between the measured and the predicted state variables: three phase currents and rotor speed. The scheme is evaluated firstly with different motor sizes and different load levels by simulation tests and then by the experimental data of the induction motors under normal operating condition at different load levels and fault

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conditions. The results from both tests show that the new scheme can estimate the parameters and predict the motor condition with sufficient accuracy for motor fault diagnosis.

**Keywords:** Induction Motor, Parameter Estimation, Genetic Algorithm, Condition Monitoring, Fault Detection

1. Introduction

Induction motors are the most widely used motors among different electric motors because of high level of reliability, efficiency and safety. Condition monitoring of induction motors can provide useful information so that the motor fault, if any, can be fixed at the earliest opportunity without affecting the plant requirement. Among many condition monitor methods such as vibration analysis, current signature processing, etc an online estimation of the motor parameters (stator and rotor resistance, stator and rotor reactance and magnetizing reactance) at a regular interval are the most potential approach to the diagnosis of the motor conditions with real engineering sense and real-time implementation. In addition, parameter estimation is the primary task for develop an automatic motor diver system. This means that the parameter estimation is important for both condition monitoring and control.

Conventionally, the parameter estimation is conducted by 3 classical tests: a locked-rotor test, a no-load test, and a DC test. However, these tests need special equipments and they are intrusive in nature and to be conducted under off-line condition. Thus, these tests may not always be feasible for the condition monitoring.

Considering the above limitations, a reliable and non-intrusive method is needed to estimate the motor parameters. Many such methods have been investigated over last several decades. Recursive Least-Square (RLS) has been applied to estimate motor parameters [1]-[3]. Treetrong et al. [1] have used to estimate the stator related parameters using the RLS method. Horga et al. [2] have used the RLS method for the squirrel-cage induction motor related parameters. They used algorithm of the continuous parametric model of the induction motor. The model was based on a technique that used the Poisson moment functional theory. The RLS was also applied to determine the rotor resistance, self-inductance of the rotor winding, and the stator leakage inductance of a three-phase induction machine [3].

Extended Kalman Filter (EKF) is another optimization technique used earlier to determine the motor parameters [4], [5]. Velazquez et al. [4] have used the EKF method to identify the speed of an induction motor and rotor flux based on the measured quantities such as stator currents and DC link voltage. The model is performed at a synchronous rotating reference frame. In another study [5], the EKF is used to estimate speed of induction motor from speed-sensorless field-oriented control and direct-torque control of induction motors. The model can be estimated at a wide velocity range and persistent zero-speed operation.

Genetic Algorithm (GA) is one of intelligent search technique to find optimized solution for a variety of complex problems. The method has also been applied to estimate the motor parameters which observed to produce good accuracy of estimation [6]-[10], compared with conventional
recursive method. In fact, in absence of the actual values of the rotor and stator related parameters in healthy condition, one can estimate these parameters using the motor specifications generally listed in the nameplate by the earlier studies based on the GA method [6], [7]. Huang et al. [8], [9] estimated all motor parameters for the motor model in the Park’ d-q reference frame. The estimation uses fewer measurements but was just validated on simulation and it requires data during machine transient operation. However, the proposed GA method for the parameters estimation is different from the earlier studies. This study has used a new scheme on the parameter estimation by using 3-phase current and voltage signals and rotor speed during normal motor operation. It is practically more viable for any condition monitoring method as there is no requirement of the machine transient operation.

Thus, this paper presents a model of the motor to estimate the motor parameters using the proposed GA method. The model is arranged from the flux linkage models and torque model of a squirrel-cage induction motor. The proposed GA method is used as a key algorithm to find the best parameter values. The fitness value is partly used to select the next generation of population. Simulation study is conducted with 3 different motor sizes and 5 different load levels of the induction motor. Having established the proposed method on the simulated examples, the method has then been applied to the experimental data of the two identical 3-phase induction motors under normal operating condition at different load. The results show that the proposed method can estimate the motor parameters effectively and indicate the motor condition with reliability.

2. Dynamic Model of Induction Motors

The dynamic model employed in this paper is the Krause’s model [11]. It formulizes the electromagnetic relation of the induction motor with a set of flux differential equations, rather than the voltage equations, which is used in most of the previous work for parameter estimation. In particular, this model is adapted to the per-unit system and does not need to calculate inverse matrix. Therefore, it has fewer problems with numerical solution and can be more efficiently, compared with the current equations. The dynamic model written in magnetic flux linkage $F$ in QD0 reference frame can be derived as Eq.1-5,

$$\frac{dF_{qr}}{dt} = \frac{\omega_r - \alpha_h}{\alpha_h} F_{qr} + \frac{R_s}{x_s} \left( \frac{x_s}{x_p} F_{qr} + \left( \frac{x_s}{x_p} - 1 \right) F_{qr} \right)$$ (1)

$$\frac{dF_{qs}}{dt} = \frac{\omega_r - \alpha_h}{\alpha_h} F_{qs} + \frac{R_s}{x_s} \left( \frac{x_s}{x_p} F_{qs} + \left( \frac{x_s}{x_p} - 1 \right) F_{qs} \right)$$ (2)

$$\frac{dF_{Is}}{dt} = \omega_h \left( \frac{v_{Is}}{x_s} F_{Is} \right)$$ (3)

$$\frac{dF_{Ir}}{dt} = \frac{\omega_r - \alpha_h}{\alpha_h} F_{Ir} + \frac{R_s}{x_s} \left( \frac{x_s}{x_p} F_{Ir} + \left( \frac{x_s}{x_p} - 1 \right) F_{Ir} \right)$$ (4)

$$\frac{dF_{Iq}}{dt} = \frac{\omega_r - \alpha_h}{\alpha_h} F_{Iq} + \frac{R_s}{x_s} \left( \frac{x_s}{x_p} F_{Iq} + \left( \frac{x_s}{x_p} - 1 \right) F_{Iq} \right)$$ (5)

Where rotor speed is $\omega_r$

$$\frac{d\omega_{r, per unit}}{dt} = \left( \frac{P}{2J} \right) \left( T_e - T_L \right)$$ (6)

The electric torque of the induction motor can be expressed by

$$T_e = \frac{3}{2} \left( \frac{P}{2} \right) \frac{1}{\omega_h} \left( F_{Ir} i_{Ir} - F_{Iq} i_{Iq} \right)$$ (7)
The base angular frequency $\omega_b = 2 \times \pi \times 50$ and the motor parameters to be estimated: $R_s, R_r, x_m, x_{ls}$ and $x_{lr}$ denoting stator resistance, rotor resistance, magnetizing reactance, stator leaking reactance and rotor leaking reactance respectively.

Eq. 1-6 are nonlinear differential equations. The solutions: $F_{qs}, F_{ds}, F_{qr}, F_{dr}, F_{os}, \omega_{r, \text{perunit}}$ can be found easily through a fourth-order Runge-Kutta method. From the solutions of the model, the stator and rotor currents in $DQ0$ reference frame can be calculated explicitly:

\[
i_{qs} = \left( \frac{1}{x_b} \right) \left( F_{qs} - x_{qs} \left( \frac{F_{qr}}{x_b} + \frac{F_{dr}}{x_{lr}} \right) \right)
\]

\[
i_{ds} = \left( \frac{1}{x_b} \right) \left( F_{ds} - x_{ds} \left( \frac{F_{dr}}{x_b} + \frac{F_{dr}}{x_{lr}} \right) \right)
\]

\[
i_{0s} = \left( \frac{1}{x_b} \right) (F_{0s})
\]

\[
i_{qr} = \left( \frac{1}{x_{lr}} \right) \left( F_{qr} - x_{qr} \left( \frac{F_{dr}}{x_{ls}} + \frac{F_{dr}}{x_{lr}} \right) \right)
\]

\[
i_{dr} = \left( \frac{1}{x_{lr}} \right) \left( F_{dr} - x_{dr} \left( \frac{F_{dr}}{x_{ls}} + \frac{F_{dr}}{x_{lr}} \right) \right)
\]

where

\[
x_{ml} = \left( \frac{1}{x_a} + \frac{1}{x_b} + \frac{1}{x_c} \right)^{-1}
\]

\[
\omega_{\text{rad/Sec}} = \frac{\omega_{r, \text{perunit}} \rho_b}{2P}
\]

In order to calculate the fitness values in applying GA, variables in $QD0$: $i_{qs}, i_{ds}$ and $i_{0s}$ are transformed into 3 phase currents by a transformation matrix $K_s$

\[
i_{abc} = i_{qds} K_s = [i_a \ i_b \ i_c]
\]

Where

\[
i_{qds} = \begin{bmatrix} i_q & i_d & i_0 \end{bmatrix}
\]

\[
K_s = \begin{bmatrix} \cos(\theta) & \sin(\theta) & 1 \\ 
\cos(\theta-(2\pi/3)) & \sin(\theta-(2\pi/3)) & 1 \\ 
\cos(\theta+(2\pi/3)) & \sin(\theta+(2\pi/3)) & 1 
\end{bmatrix}
\]

where $\theta = 0^o$, for the stationary frame used when the currents in $DQ0$ are transformed into $ABC$ reference frame. The 3–phase voltages are used as measurement data to input the model. The model will produces 3 phase currents and rotor speeds called predicted data. The proposed GA method is used to search the best motor parameters by comparing the measured and predicted data by Eq. 15 (attempt to find minimum error).

### 3. Parameter Estimation Based on GA

A Genetic Algorithm (GA) is a search technique used in computing to find solution in optimization problems [12], [13]. It applies the principles of evolution found in nature to the problem of finding an optimal solution to a Solver problem. In a “genetic algorithm,” the problem is usually encoded in a series of bit strings that are manipulated by the algorithm. The algorithm of the parameter estimation programming can be expressed in Figure 1.

**A. An initial population creation of parameters.** It is based on randomness. $P_{00}$ is generated with randomly selected individuals. Each individual parameter is constrained by the following condition

\[
P_{\text{min}} \leq P_j \geq P_{\text{max}}, \ i = 1,2,\ldots,n \text{ and } j = 1,2,\ldots,m
\]
where $P_{\text{min}}$ and $P_{\text{max}}$ are the limits of the parameter vector values. $n$ is maximum numbers of generation and $m$ is number of parameters or variables. After randomly generating initial population, they will be transformed into binary number. Simultaneously, the $ABC$-reference frame voltage $(v_{sa}, v_{sb}, v_{sc})$ are sent to the estimation model. The estimation model produces $dq0$-reference frame currents $(i_{sd}, i_{sq}, i_{s0})$ and rotor speeds $(\omega_r)$. The currents are transformed back into $ABC$-reference frame currents and the rotor speeds are transformed into radian per second unit. The only 1 stator phase current and rotor speed are used to estimate the parameters by which they are used to calculate the error (Eq. 16) by comparing them with the measured currents and the rotor speeds collected from the induction motor.

**B. Evaluation Operation.** Firstly, the binary number of each parameter will be transformed back into decimal number. Then, each individual is used to calculate the error from objective function. The error of objective function can be shown as

$$E(ngen,t) = Y(ngen,t) - \bar{Y}(ngen,t)$$  

where and $Y(t) = [i_{sa} \quad \omega_r]$ and $\bar{Y}(t) = [\bar{i}_{sa} \quad \bar{\omega}_r]$ where vectors $Y$ are measured data and $Y$ are estimated data.

$$\text{Futbess} (ngen) = \sum_{t=0}^{t_{\text{max}}} E(ngen,t)^T \Lambda E(ngen,t)$$  

where $\Lambda$ is a unit matrix, $t$ is sampling time

**C. GA procedures: selection, Crossover, Mutation Operation.** The Probability of Crossover, $P_c$ is 0.80 and Probability of Mutation, $P_m$ is 0.001 in this paper. The next generation (offspring) from their parent will be produced from this GA operation. They are used to calculate for next iteration. The program will be terminated if the minimal error from objective function or the maximal number of generation is reached.

**4. Simulation Study**

A program of the motor parameters estimation is developed in Matlab code. It is important to define the range of parameters - $P_{\text{min}}$ and $P_{\text{max}}$ to start the computation. In the simulation study, the maximum generation number was set up at 200 and the population size equal to 10. The measured data of stator voltages, currents and rotor speeds were collected from steady state period. Simulation test were conducted with 3 different types of the induction motors. The specifications of each motor.
The results in simulation test show good accuracy of estimation. The population and generation sizes can improve the accuracy, but it will increase the time of the estimation. However, this test has been done without voltage unbalance and measurement noises. These factors can affect the accuracy of estimation.
This test, maximum generation was set up at 200 and population number as 10. The data are also collected from 5 different load levels and 3 different conditions (healthy, rotor fault and stator faults). The stator fault motor (Motor 2) can be divided into open circuit (healthy), 5 turn short circuit, 10 turn short circuit, 15 turn short circuit. During experiments, several sets of the stator voltage, current and rotor speed data were collected at

\[ R_s = 1.7056 \, \Omega, \quad R_r = 1.0020 \, \Omega, \quad x_{ls} = 0.8553 \, \Omega, \quad x_{lr} = 0.8553 \, \Omega, \quad x_m = 40.1854 \, \Omega \]

<table>
<thead>
<tr>
<th>Phase</th>
<th>Power</th>
<th>Voltages</th>
<th>f</th>
<th>PF</th>
</tr>
</thead>
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<tr>
<td>M1</td>
<td>3</td>
<td>Δ230/Y400</td>
<td>50</td>
<td>0.75</td>
</tr>
<tr>
<td>M2</td>
<td>3</td>
<td>Δ230/Y400</td>
<td>50</td>
<td>0.75</td>
</tr>
</tbody>
</table>

M1 = Rotor Fault Motor, M2 = Healthy and Stator Fault Motor
different times. The average values of the estimation results will be expressed. The estimated results are shown in Table 6-10. It can be seen from all tables, the estimated parameters for the healthy case are close to the actual values irrespective of load conditions. For the faulty stators, the estimated parameters related to the stator only are decreasing and the rotor parameters are remain close to the healthy values, and similar observations have been made for the rotor faults. Hence the suggested approach is robust for the experimental cases as well where the signals are expected to have some measurement noise. Unfortunately, both the rotor and stator faults were not simulated simultaneously in the experiments to further enhance the confidence level in the suggested approach.

### Table 6 The estimated parameters for the experimental case (0 % Load)

<table>
<thead>
<tr>
<th>25% Load</th>
<th>( R_s )</th>
<th>( X_{sh} )</th>
<th>( R_r )</th>
<th>( X_{lr} )</th>
<th>( X_m )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Value</td>
<td>1.7056</td>
<td>0.8553</td>
<td>1.0020</td>
<td>0.8553</td>
<td>40.1854</td>
</tr>
<tr>
<td>Estimated Parameters</td>
<td>Healthy</td>
<td>1.5744</td>
<td>0.9577</td>
<td>0.9170</td>
<td>0.8344</td>
</tr>
<tr>
<td></td>
<td>5 Turn Short</td>
<td>0.8654</td>
<td>0.6944</td>
<td>0.9554</td>
<td>0.8656</td>
</tr>
<tr>
<td></td>
<td>10 Turn Short</td>
<td>0.5776</td>
<td>0.4875</td>
<td>0.8944</td>
<td>0.8767</td>
</tr>
<tr>
<td></td>
<td>15 Turn Short</td>
<td>0.3355</td>
<td>0.3233</td>
<td>1.0436</td>
<td>0.8891</td>
</tr>
<tr>
<td></td>
<td>Broken Bars</td>
<td>1.5500</td>
<td>0.9945</td>
<td>1.5237</td>
<td>1.2741</td>
</tr>
</tbody>
</table>

Unit: Ohm (Ω)

### Table 7 The estimated parameters for the experimental case (25 % Load)

<table>
<thead>
<tr>
<th>25% Load</th>
<th>( R_s )</th>
<th>( X_{sh} )</th>
<th>( R_r )</th>
<th>( X_{lr} )</th>
<th>( X_m )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Value</td>
<td>1.7056</td>
<td>0.8553</td>
<td>1.0020</td>
<td>0.8553</td>
<td>40.1854</td>
</tr>
<tr>
<td>Estimated Parameters</td>
<td>Healthy</td>
<td>1.5912</td>
<td>0.9170</td>
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<td>0.8476</td>
</tr>
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<td>5 Turn Short</td>
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<td>0.6450</td>
<td>0.9446</td>
<td>0.8487</td>
</tr>
<tr>
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<td>10 Turn Short</td>
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<td>0.4988</td>
<td>0.9385</td>
<td>0.8590</td>
</tr>
<tr>
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<td>15 Turn Short</td>
<td>0.3155</td>
<td>0.2806</td>
<td>0.9243</td>
<td>0.8566</td>
</tr>
<tr>
<td></td>
<td>Broken Bars</td>
<td>1.5632</td>
<td>0.9237</td>
<td>1.4931</td>
<td>1.3351</td>
</tr>
</tbody>
</table>

Unit: Ohm (Ω)

### Table 8 The estimated parameters for the experimental case (50 % Load)

<table>
<thead>
<tr>
<th>50% Load</th>
<th>( R_s )</th>
<th>( X_{sh} )</th>
<th>( R_r )</th>
<th>( X_{lr} )</th>
<th>( X_m )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Value</td>
<td>1.7056</td>
<td>0.8553</td>
<td>1.0020</td>
<td>0.8553</td>
<td>40.1854</td>
</tr>
<tr>
<td>Estimated Parameters</td>
<td>Healthy</td>
<td>1.5912</td>
<td>0.9170</td>
<td>0.9577</td>
<td>0.8476</td>
</tr>
<tr>
<td></td>
<td>5 Turn Short</td>
<td>0.8654</td>
<td>0.6450</td>
<td>0.9446</td>
<td>0.8487</td>
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<tr>
<td></td>
<td>10 Turn Short</td>
<td>0.5776</td>
<td>0.4988</td>
<td>0.9385</td>
<td>0.8590</td>
</tr>
<tr>
<td></td>
<td>15 Turn Short</td>
<td>0.3155</td>
<td>0.2806</td>
<td>0.9243</td>
<td>0.8566</td>
</tr>
<tr>
<td></td>
<td>Broken Bars</td>
<td>1.5632</td>
<td>0.9237</td>
<td>1.4931</td>
<td>1.3351</td>
</tr>
</tbody>
</table>

Unit: Ohm (Ω)

### Table 9 The estimated parameters for the experimental case (75 % Load)

<table>
<thead>
<tr>
<th>75% Load</th>
<th>( R_s )</th>
<th>( X_{sh} )</th>
<th>( R_r )</th>
<th>( X_{lr} )</th>
<th>( X_m )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Value</td>
<td>1.7056</td>
<td>0.8553</td>
<td>1.0020</td>
<td>0.8553</td>
<td>40.1854</td>
</tr>
<tr>
<td>Estimated Parameters</td>
<td>Healthy</td>
<td>1.5904</td>
<td>0.9457</td>
<td>0.9489</td>
<td>0.8344</td>
</tr>
<tr>
<td></td>
<td>5 Turn Short</td>
<td>0.8790</td>
<td>0.6309</td>
<td>0.9409</td>
<td>0.8211</td>
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<td></td>
<td>10 Turn Short</td>
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<td>0.8598</td>
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<tr>
<td></td>
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<td>0.8133</td>
</tr>
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<td></td>
<td>Broken Bars</td>
<td>1.5650</td>
<td>0.9001</td>
<td>1.3945</td>
<td>1.2922</td>
</tr>
</tbody>
</table>

Unit: Ohm (Ω)

### Table 10 The estimated parameters for the experimental case (100 % Load)

<table>
<thead>
<tr>
<th>100% Load</th>
<th>( R_s )</th>
<th>( X_{sh} )</th>
<th>( R_r )</th>
<th>( X_{lr} )</th>
<th>( X_m )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Value</td>
<td>1.7056</td>
<td>0.8553</td>
<td>1.0020</td>
<td>0.8553</td>
<td>40.1854</td>
</tr>
<tr>
<td>Estimated Parameters</td>
<td>Healthy</td>
<td>1.5766</td>
<td>0.9170</td>
<td>0.9577</td>
<td>0.8795</td>
</tr>
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<td>0.8370</td>
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<tr>
<td></td>
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<td>0.4944</td>
<td>0.9671</td>
<td>0.8297</td>
</tr>
<tr>
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<td>0.2896</td>
<td>0.9473</td>
<td>0.8534</td>
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<td>Broken Bars</td>
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<td>0.9257</td>
<td>1.3730</td>
<td>1.2678</td>
</tr>
</tbody>
</table>

Unit: Ohm (Ω)

Figure 3-4 show typical comparison of the stator phase current and rotor speeds both the measured and the estimated data during iterative process. The steady state period of the data are used while estimation.
Figure 3  A typical comparisons of the measured and the estimated stator phase current from phase A.

Figure 4  The rotor speed from measured and estimated data.

Figure 5  The convergence of the Objective Function with Generation for the healthy Motor-2 at 100% load.

Figure 6  Parameters estimation vs Generation for the healthy Experimental Motor-2 at 100% load; (a) $R_s$, (b) $x_{ls}$, (c) $R_r$, (d) $x_{ir}$, and (e) $x_m$.

6. Conclusions

A model is arranged from the flux linkage models and torque model of a squirrel-cage induction motor. The proposed GA method is applied as a key technique to estimates the motor parameters: stator and rotor resistance, stator and rotor reactance, and magnetizing reactance. The
only 2 measurements (stator phase current and rotor speed) during the machine normal operation were used as the input data. The simulations were used to evaluate the proposed method and then the method has further been validated through the experiments on the induction motors. The motor faults (stator and rotor faults) can be detected by observing the change in the parameters. It means that if the change in the parameters has been detected from original values, the faults are happening in the motor. The severity level of the faults can be calculated from the parameter change. The voltage unbalances from the motor installed at site in some cases may slightly affect the accuracy of the estimation. Thus, the further development is also under way.

References


