

Impact of Induction Motor Faults on the Basic Parameters' Values

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ABSTRACT

Unlike fault diagnosis approaches based on the direct analysis of current and voltage signals, this paper proposes a diagnosis of induction motor faults through monitoring the variations in motor's parameters when it is subjected to an open circuit or short circuit faults. These parameters include stator and rotor resistances, self-inductances, and mutual inductance. The genetic algorithm and the trust-region method are used for the estimation process. Simulation results confirm the efficiency of both the genetic algorithm and the trust-region method in estimating the motor parameters; however, better performance in terms of estimation time is obtained when the trust-region method is adopted. The results also show the possibility of extracting fault signatures from the motor's parameter values because each type of the mentioned faults has a different impact on these parameters. Under a 10% short circuit fault condition, the mutual inductance and rotor resistance deviate by almost 10% from their original values to lower values. While the stator resistance noticeably reduces by up to 20% during the open circuit fault condition.

Keywords: Induction Motor, Fault Diagnosis, Open Circuit Fault, Short Circuit Fault.

تأثير أعطال المحرك الحثي على قيم معاملاته الأساسية

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الخلاصة

على عكس طرق التشخيص التي تعتمد على التحليل المباشر لأشارات التيار والجهد، هذه الورقة تقترح تشخيص أعطال المحرك الحثي من خلال مراقبة التغيرات في القيم لمعاملات المحرك عندما يتعرض لأعطال الدائرة المفتوحة والدائرة المقصورة. هذه المعاملات تتضمن المقاومات و المحاثات للجزء الثابت والمتحرك والمحاثة المشتركة. تم استخدام الخوارزمية الجينية و طريقة منطقة-الثقة في عملية التخمين. تؤكد نتائج المحاكات كفاءة كل من الخوارزمية الجينية و طريقة منطقة الثقة في تخمين قيم

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Peer review under the responsibility of University of Baghdad.

<https://doi.org/10.31026/j.eng.2020.12.04>

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Article received: 17/5/2020

Article accepted: 26/7/2020

Article published:1/12/2020



معاملات المحرك، غير أن أفضل أداء من حيث زمن التخمين، تم الحصول عليه باستخدام طريقة منطقة-الثقة. وايضا أظهرت النتائج إمكانية أستخلاص علامات العطل من قيم معاملات المحرك لأن كل نوع من الاعطال المذكورة له تأثير مختلف على هذه المعاملات. تحت ظرف عطل الدائرة المقصورة بشدة 10%، المحاطة المشتركة ومقاومة الجزء المتحرك تتحرف بقرابة 10% من قيمها الأصلية إلى قيم أقل. بينما مقاومة الجزء الثابت، تقل بصورة ملحوظة بنسبة تصل إلى 20% خلال ظرف عطل الدائرة المفتوحة.

الكلمات الرئيسية: المحرك الحثي، تشخيص العطل، عطل الدائرة المفتوحة، عطل الدائرة المقصورة .

1. INTRODUCTION

According to a study presented in 2011, the number of electrical machines, which are used around the world, is 16.1 billion. Three-phase induction motors represent 60% of the total number; hence, they have a special position in the energy conversion owing to their merits such as robustness, low cost, and high performance (Garcia-guevara et al., 2016). These motors' reliability is mainly affected when a fault occurs; therefore, the diagnosis of fault becomes a significant subject in recent years (Rajamany et al., 2019). Induction motors suffer from stator and rotor faults by percentages of 37% and 10%, respectively. Thermal, mechanical, and environmental stresses are the leading causes of these faults (Tang et al., 2020). As stator faults have a high percentage of occurrence, many publications are focused on developing strategies for diagnosing them (Garcia-guevara et al., 2016), (Guezmil et al., 2019) and (Angelo et al., 2009).

The worst types of stator faults are phase to ground and phase-to-phase faults. These faults generally start with undetectable inter-turn short circuit fault (Khader, Champenois, et al., 2018). Such fault is responsible for generating high currents and winding overheating that may damage the stator core (Angelo et al., 2009). Moreover, a small short circuit between several turns in the same winding can result in a critical open circuit fault (Ethni et al., 2018). The later fault is subjecting the machine to severe voltage unbalance like a three-phase induction motor fed from a single-phase voltage source (Ferreira et al., 2018). The operating induction motor under this asymmetry has two rotating fields: the forward rotating field created by the positive sequence current and the backward rotating field induced by the negative sequence current, resulting from an unbalanced supply voltage. Consecutively, the collaboration of these fields generates velocity disturbances and pulsating electromagnetic torque, which increases losses and noise in the motor (Mirabbasi et al., 2009). Therefore, detecting the faults from their initial stage is crucial (Garcia-guevara et al., 2016), (Ethni et al., 2018) and (Abd Alhassan et al., 2017).

Detection of induction motor stator winding faults has been proposed in different strategies. Ben et al. suggested a technique for separating the negative sequence current (NSC) generated due to the machine's asymmetry and NSC generated because of the inter-turn fault, hence, detecting the fault by monitoring of the negative sequence current (Khader et al., 2018). In (Guezmil et al., 2019), an observer-based approach has been utilized for generating a residual value. Fault detection of an inter-turn fault is alarmed when this value is greater than a pre-set threshold value. Recently, a review paper states that motor faults can be addressed efficiently using an inverse problem theory. Hence, instead of directly analyzing the machine's current and/or voltage signals to extract their signatures to detect a fault, the inverse problem theory uses the machine parameters themselves as a fault identifier (Asad et al., 2018). Thus, this paper adopted the inverse problem theory to study the effects of short circuit and open circuit faults on an induction motor's parameters. To validate this proposal, Matlab/ Simulink software has been used for motor parameter estimation. Two optimization methods, genetic algorithm and trust-region method, are adopted, and their performances in terms of the processing time are evaluated.

The organization of this paper is as follows. Section 2 illustrates the strategy for estimating the basic parameters' values under the presence of the motor's faults. The optimization methods, which are employed for the estimation, are given in section 3. The simulation results are shown in section 4. Finally, the paper is concluded in section 5.

2. STRATEGY FOR PARAMETERS ESTIMATION

According to the inverse problem theory, the system model's parameters can be estimated from the real system's observed output data (Asad et al., 2018). Hence, to study the effect of short circuit and open circuit faults on the basic parameters of an induction motor (stator and rotor resistances (r_s , r_r), inductances (L_{1s} , L_{1r}) and mutual inductance (L_m)), the schematic diagram shown in Fig. 1 is suggested. As illustrated in Fig. 1, for estimating the basic parameters of a healthy motor model, an optimization method can be used to reduce the errors between the collected stator currents data and the model stator currents data. From the control theory aspect, the parameters estimation process offers a closed-loop structure with respectable computational stability and convergence (Sun et al., 2020). Therefore, the estimated values of the basic parameters can be used for fault detection.

The healthy motor model and other faulty models with short circuit and open circuit faults to represent a practical induction motor are developed from (Arkan et al., 2005). The models are in a q-d stationary reference frame and the detailed equations will not present in this paper.

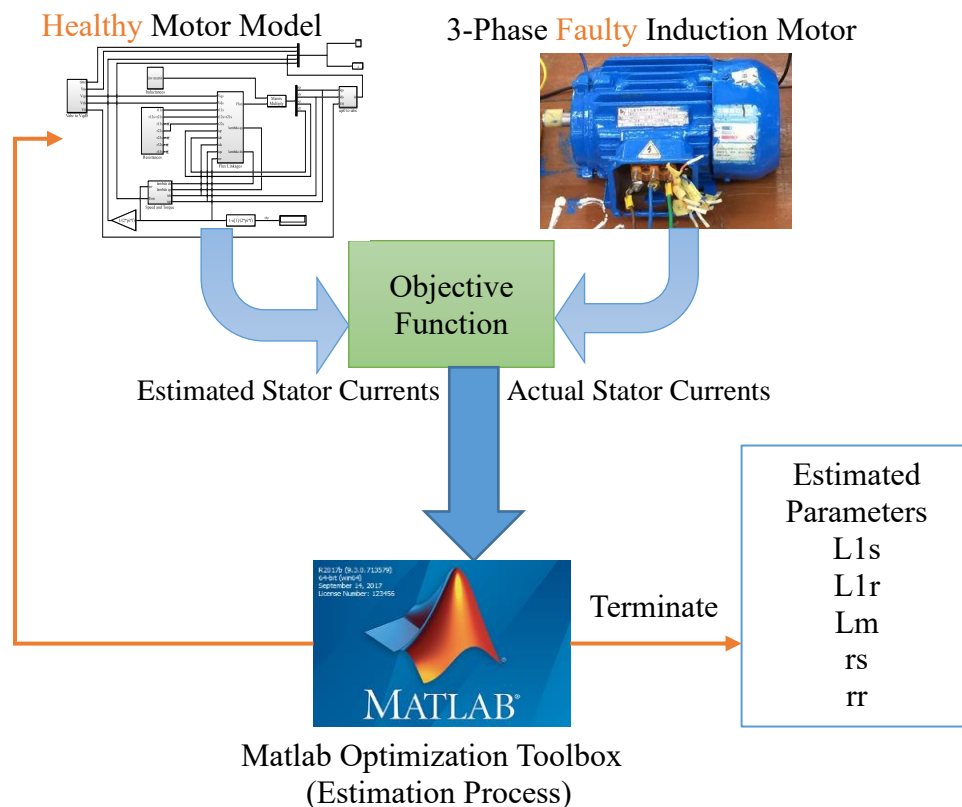


Figure 1. The schematic diagram for parameters estimation.



3. OPTIMIZATION METHODS

A three-phase induction motor is nonlinear, i.e.; the objective function presents several local minima. For comparison, two optimization methods have been selected to estimate the healthy motor model's basic parameters values. A stochastic genetic algorithm (GA) and a deterministic trust-region method (TRM).

3.1 Genetic Algorithm (GA)

The genetic algorithm is a stochastic optimization method inspired by nature "the survival for the fittest". In GA, searching for the global solution starts from a generation of random population size. Then some of the population enter the crossover and mutation operations after the selection process. The procedure of GA is clarified in **Fig. 2 (Rao, 2009)**, where $iabc$, $iabc^{\wedge}$ are the three-phase stator currents of the real induction motor and the estimated currents from the healthy motor model, respectively.

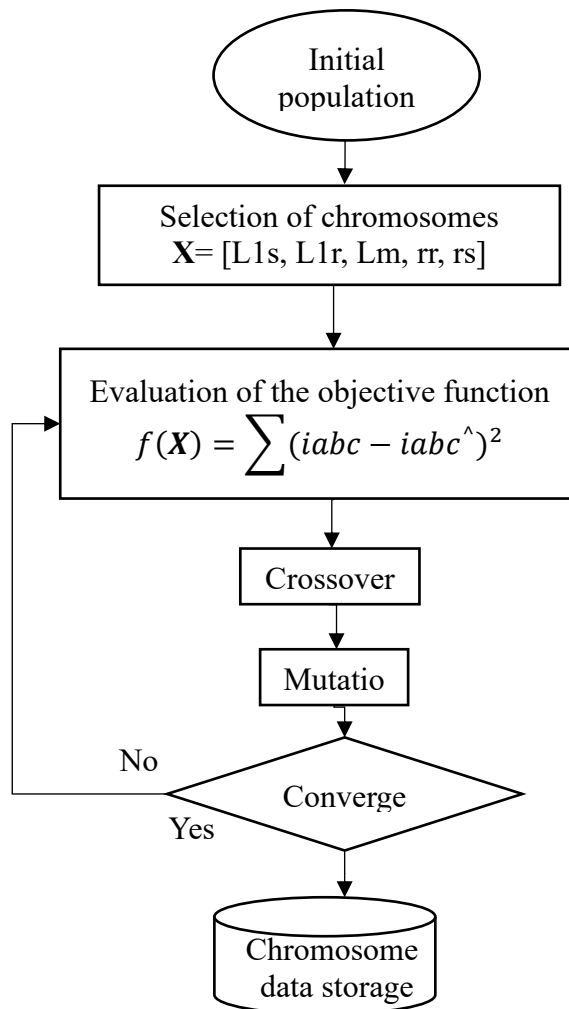


Figure 2. GA procedure.



3.2 Trust-region Method (TRM)

The trust-region method (TRM) is a deterministic optimization method. With the help of a quadratic model, TRM searches for the optimal solution by defining a trustable region around the existing iteration and then iterates until the convergence condition is met (Choi et al., 2005). The procedure of TRM is given as follows (Yang et al., 2015):

1- Initiate a trust-region boundary with an initial radius $\Delta_0 > 0$: set $0 \leq \tau_1 < \tau_2 < 1, 0 \leq \tau_3 < \tau_4$, upper radius limit $\Delta^- > 0$ and $0 \leq \epsilon < 1$

2- Evaluate the gradient of the objective function Eq. (1).

$$g_k = \begin{bmatrix} \frac{\partial f(x)}{\partial ia} & \frac{\partial f(x)}{\partial ib} & \frac{\partial f(x)}{\partial ic} \end{bmatrix} \tag{1}$$

3- Solve the following quadratic subproblem to find the solution d_k :

$$\left. \begin{aligned} \min q_k(d) &= g_k^T d + \frac{1}{2} d^T B_k d \\ \text{Such that } \|d\| &< \Delta_k \end{aligned} \right\} \tag{2}$$

Where B_k is the approximate of the hessian matrix as given in Eq. (3), and $\|d\|$ is the norm of the vector d .

$$B_k = \begin{bmatrix} \frac{\partial^2 f(x)}{\partial^2 ia} & \frac{\partial^2 f(x)}{\partial^2 ia ib} & \frac{\partial^2 f(x)}{\partial^2 ia ic} \\ \frac{\partial^2 f(x)}{\partial^2 ib ia} & \frac{\partial^2 f(x)}{\partial^2 ib} & \frac{\partial^2 f(x)}{\partial^2 ib ic} \\ \frac{\partial^2 f(x)}{\partial^2 ic ia} & \frac{\partial^2 f(x)}{\partial^2 ic ib} & \frac{\partial^2 f(x)}{\partial^2 ic} \end{bmatrix} \tag{3}$$

4- Update the trust-region radius as shown in Eq. (4):

$$\Delta_{k+1} = \begin{cases} \tau_3 \Delta_k, & \text{if } r_k \leq \tau_1 \\ \Delta_k, & \text{if } \tau_1 < r_k \leq \tau_2 \\ \min\{\tau_4 \Delta_k, \Delta^-\}, & \text{if } r_k > \tau_2, \|d_k\| = \Delta_k \end{cases} \tag{4}$$

Where $r_k = \frac{f(x_k) - f(x_k + d_k)}{q_k(0) - q_k(d_k)}$

5- If $r_k > \tau_1$ then $x_{k+1} = x_k + d_k, B_{k+1} = B_k, k=k+1$ and go to step 1

Else $x_{k+1} = x_k, k=k+1$ and go to step 2

The procedure of TRM is summarized in the flowchart shown in Fig. 3.

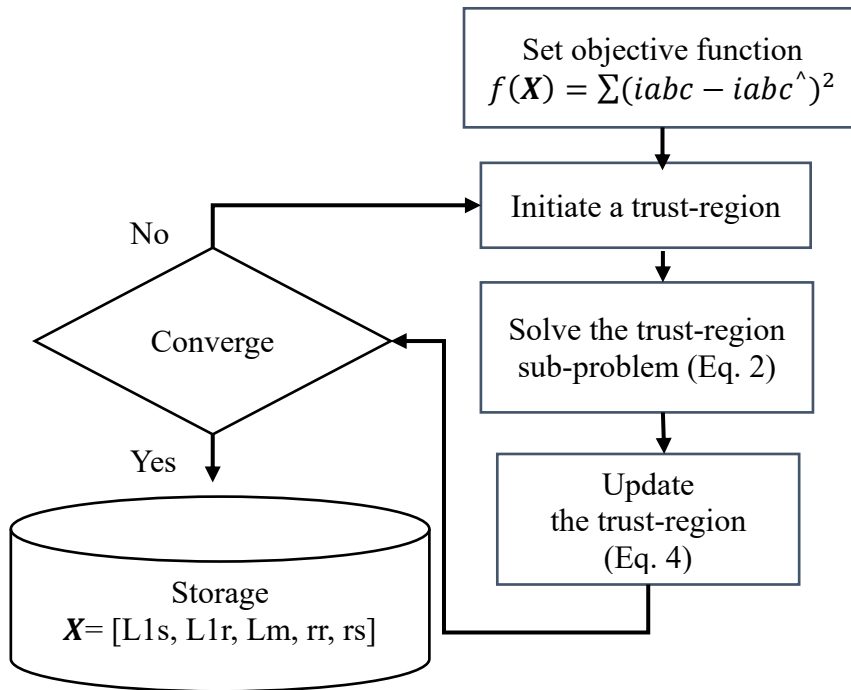


Figure 3. TRM Procedure.

4. SIMULATION RESULTS

The parameters of a 5hp three-phase induction motor are used to study the motor behavior under the presence of short circuit and open circuit faults. The motor parameters are shown in Table 1 (Mohammadi and Akhavan, 2014).

Table 1. Three-phase induction motor parameters.

Parameters	Values
Rated power	5 hp
Rated voltage	460 V
Frequency	60 Hz
Number of poles	4
Full-load power factor	0.89
Full-load torque	19.673 Nm
Stator resistance (rs)	1.115 Ω
Rotor resistance (rr)	1.083 Ω
Stator inductance (L1s)	0.003 H
Rotor inductance (L1r)	0.003 H
Mutual inductance (Lm)	0.102 H

These parameters are used to run the healthy motor model and other faulty motor models used instead of actual motor (Arkan, Kostic-perovic, and Unsworth, 2005). For each fault type (open circuit or short circuit), the faulty motor model is adapted to emulate the fault. The models are simulated in MATLAB/Simulink environment, and the built-in optimization toolbox is utilized to validate the proposal.

The full load stator currents (i_a , i_b , i_c) for the four operating conditions are presented in Fig. 4, Fig. 5, and Fig. 6, respectively. These conditions include healthy, faulty with 3% short circuit fault at phase 'a', 10% short circuit fault at phase 'a', and faulty with the phase 'a' is open circuit. It can be seen that the motor has balance stator currents during the healthy operation and unbalanced current when the motor is subjected to short circuit or open circuit faults. The faulty phase (phase 'a') current shown in Fig.1 is remarkably increasing with the increment of short circuit fault severity and has almost zero magnitude when phase 'a' is opened. However, the currents of healthy phases shown in Fig. 5 and Fig. 6 are also affected due to the presence of faults. Under the short circuit fault, the amplitude of phase 'b' and 'c' increases and decreases, respectively. Unlike the short circuit fault condition, the currents of the healthy phases (b and c) have equal amplitude and 180° apart out-of-phase when the open circuit fault occurs at phase 'a'.

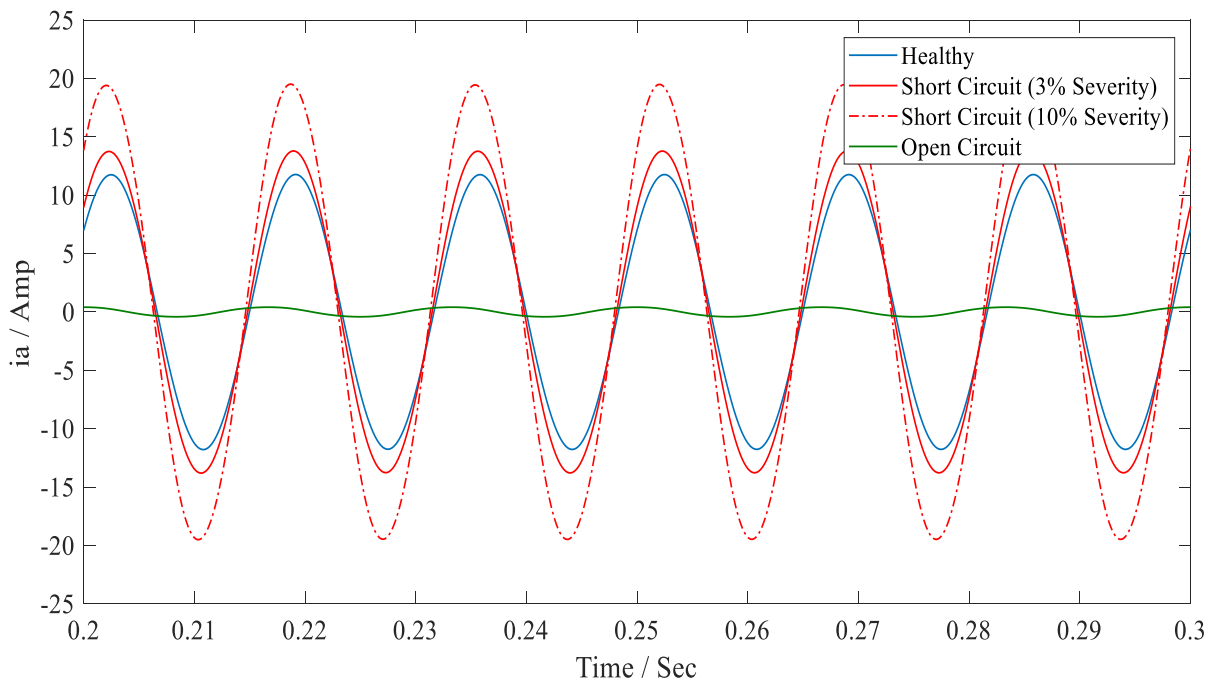


Figure 4. Phase 'a' stator current for healthy, short circuit, and open circuit conditions.

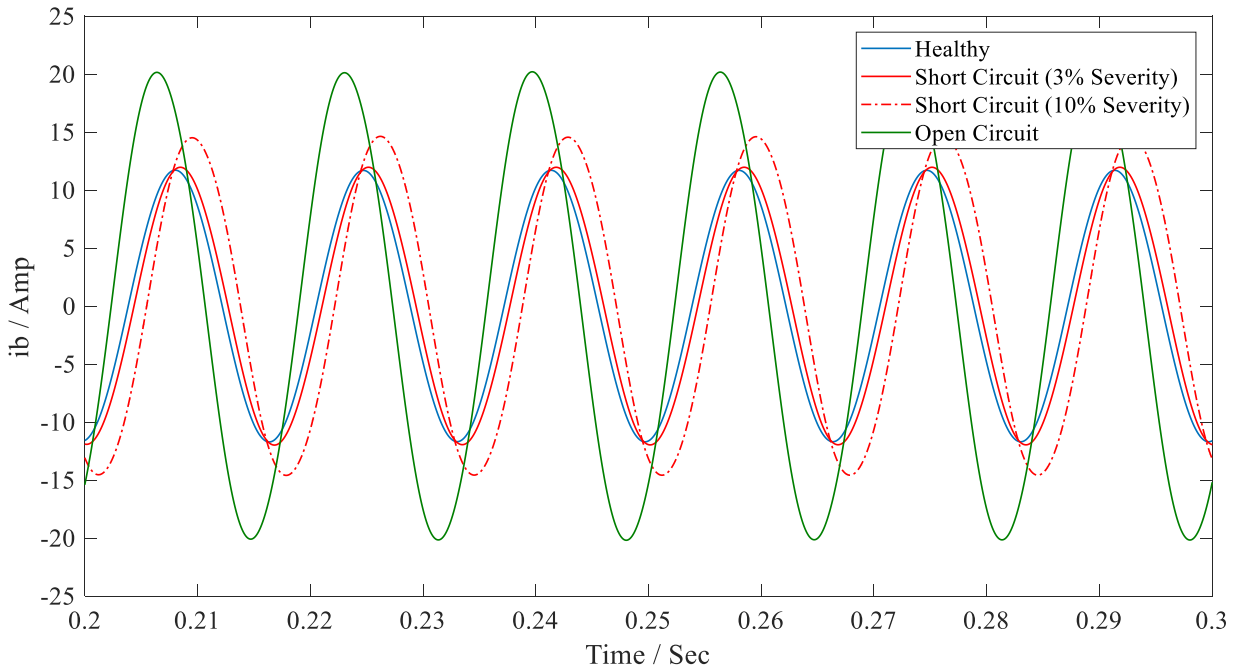


Figure 5. Phase 'b' stator current for healthy, short circuit, and open circuit conditions.

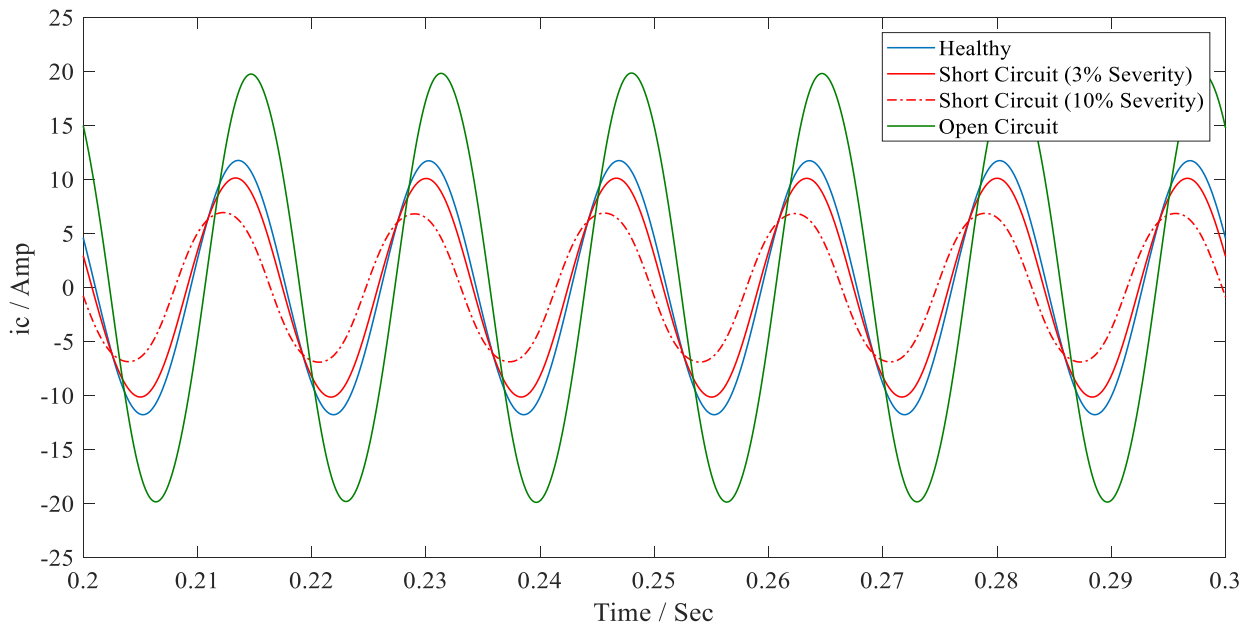


Figure 6. Phase 'c' stator current for healthy, short circuit, and open circuit conditions .

The effects of faults on the speed and electromagnetic torque are demonstrated in **Fig. 7** and **Fig. 8**, respectively. As shown in these figures, the presence of faults is reflected as a ripple, which is resulted from the interaction of the forward field generated by the positive sequence current and the backward field produced by the negative sequence current. These results are closely matched with the results of the healthy and faulty conditions presented in (Mabrek and Hemsas, 2017). Hence, the adopted models are fairly trustable to be used for parameters estimation.

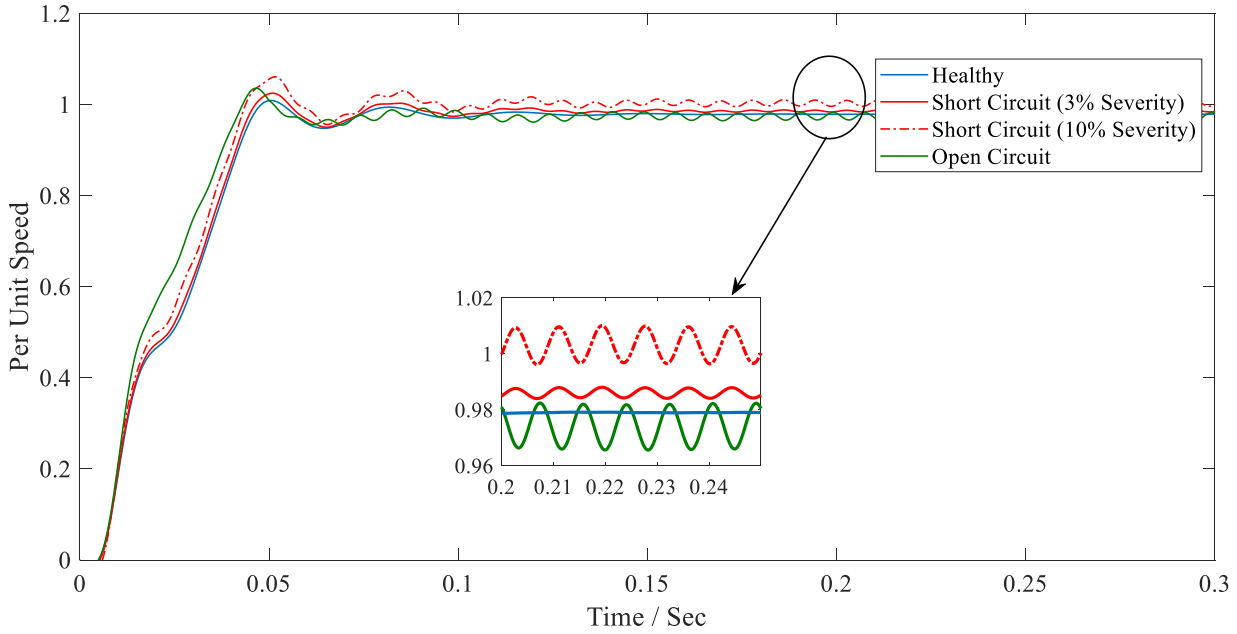


Figure 7. Per unit speed for healthy, short circuit, and open circuit conditions.

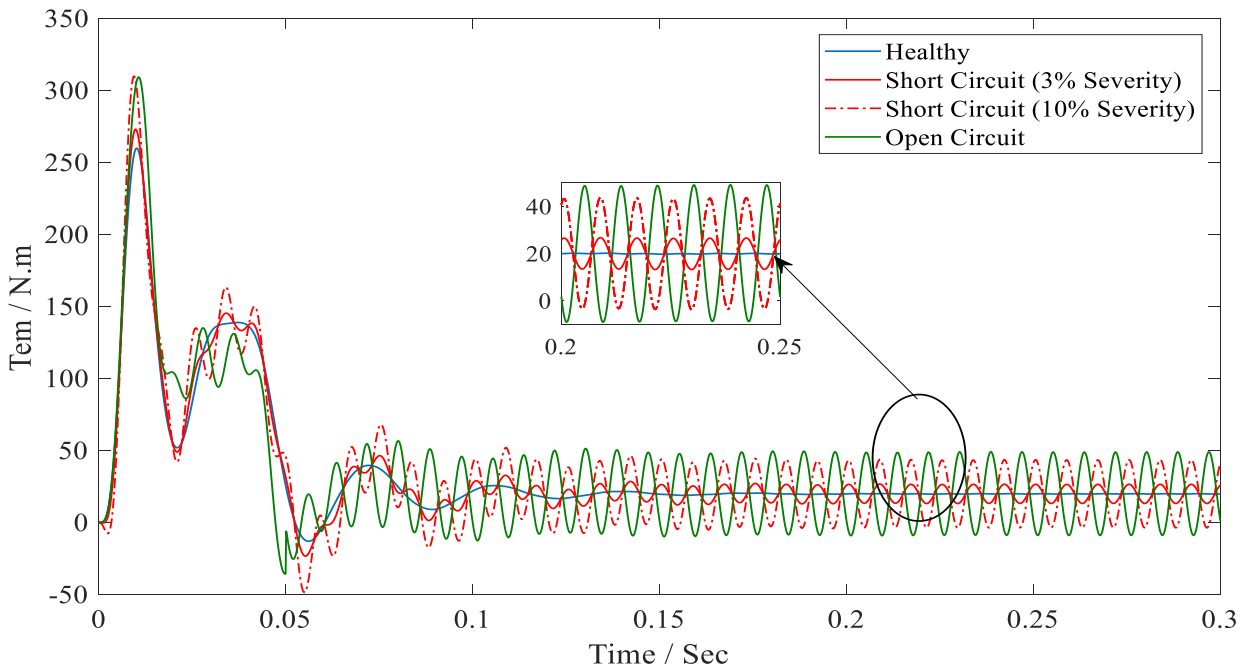


Figure 8. Electromagnetic torque for healthy, short circuit, and open circuit conditions.

To validate the proposal shown in Fig. 1, the faulty currents signals are collected from the faulty motor model (actual faulty motor model) for 1 sec. Afterward, the objective function, which is the sum-squared errors between the healthy motor currents and the faulty machine currents, is evaluated. GA and TRM solvers of Matlab-R2017 are used to minimize the objective function. The algorithms iterations are terminated when the difference between the objective function's consecutive values is less than 0.001. Fig. 9 illustrates the stator and rotor inductances (L1s and



L1r) values estimated by GA and TRM. L1s and L1r are slightly changed due to the low fault severity (3% short circuit condition), but they have a noticeable change for 10% short circuit and open circuit conditions. L1s and L1r estimated by TRM have the same attitude while their estimated values by GA appear in opposite directions under faulty conditions.

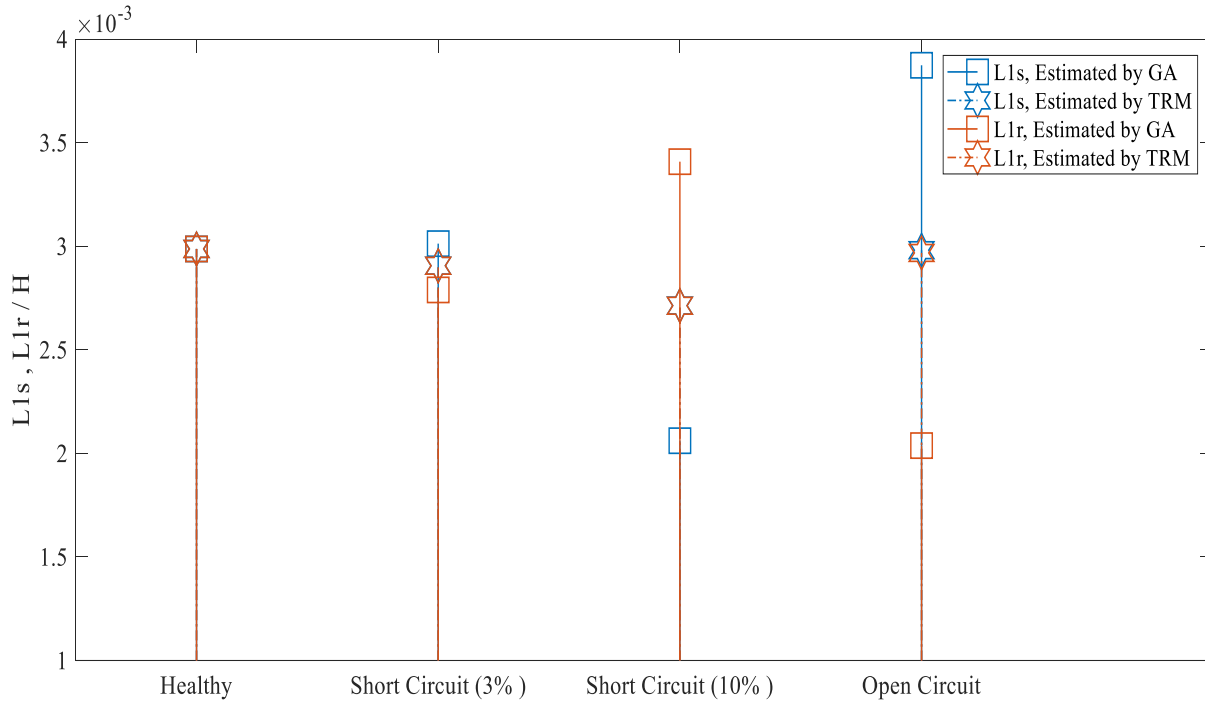


Figure 9. Estimated stator and rotor inductances by GA and TRM for healthy, short circuit, and open circuit conditions.

The mutual inductance (L_m) value estimated by GA and TRM shows that L_m decreases under short circuit fault and increases when an open circuit fault has occurred. Hence, L_m has apparent different attitudes according to the nature of the fault, as depicted in **Fig. 10**.

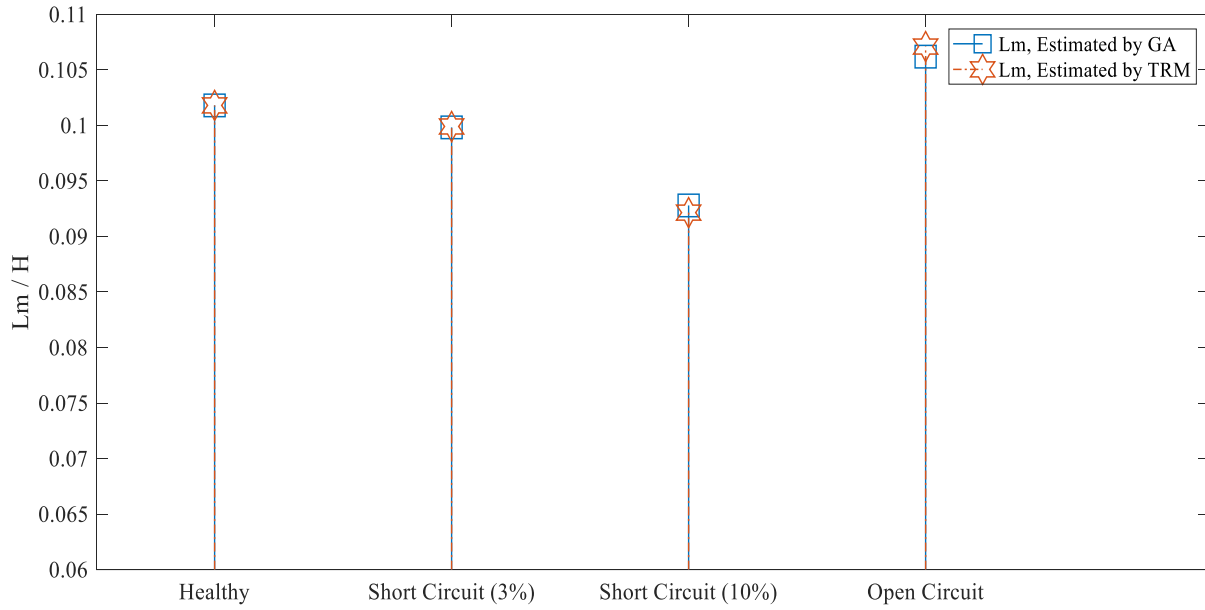


Figure 10. Estimated mutual inductance by GA and TRM for healthy, short circuit, and open circuit conditions.

The effects of short circuit and open circuit faults on the stator and rotor resistances (r_s and r_r) are illustrated in **Fig. 11**. r_s rises from its nominal value under short circuit conditions and sharply decreases under open circuit conditions from the estimated values. The reverse behavior is shown by r_r for both types of faults.

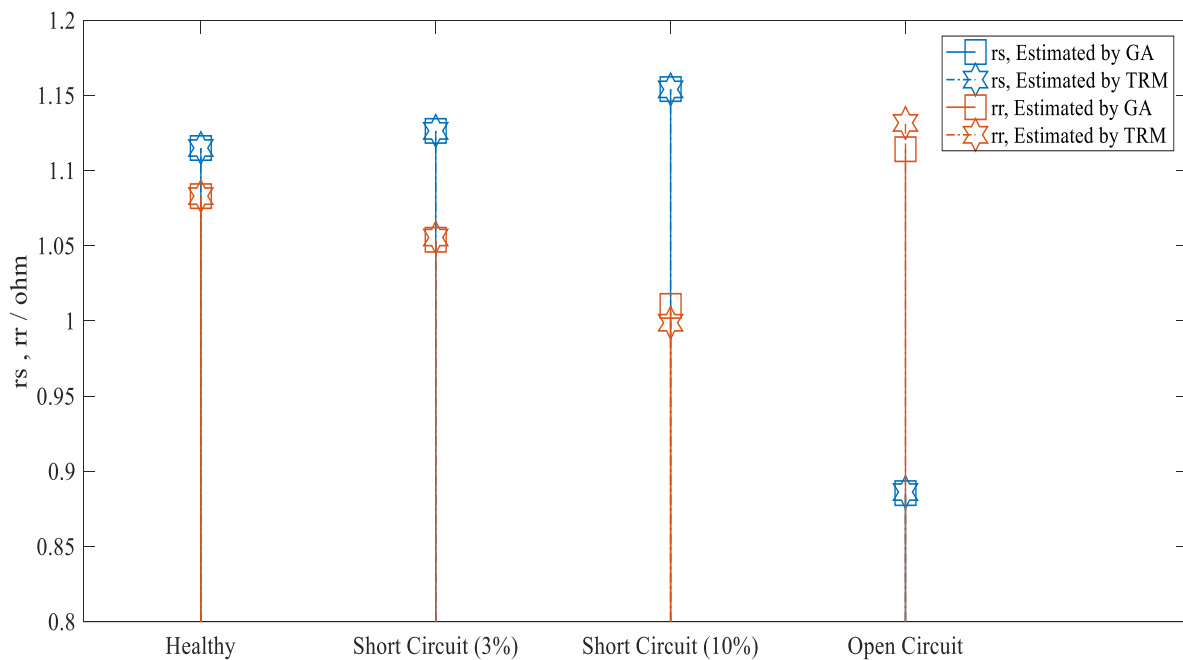


Figure 11. Estimated stator and rotor resistances by GA and TRM for healthy, short circuit, and open circuit conditions.



As shown in the above figures, both GA and TRM give almost the same estimated values of the basic parameters except for L1s and L1r. Since GA estimates these values in a reverse relationship that can be justified as the healthy phases currents of the machine suffering from the faulty conditions (**Fig. 5** and **Fig. 6**), they are changed in their amplitude and phase in the opposite relationship. i.e., GA tries to find the optimal values of the basic parameters that make the healthy model currents coincide with the actual faulty currents in their magnitude and phase. Although GA and TRM are global convergence techniques, they differ in minimizing the nonlinear objective function, as shown in **Table 2**.

Table 2. Comparison between GA and TRM in term of objective function minimization.

Estimation Method	GA	TRM
Minimization in objective function for short circuit (3%) condition	22.6746 to 21.4029	22.6746 to 21.4128
Minimization in objective function for short circuit (10%) condition	263.5958 to 246.6027	263.5958 to 248.6027
Minimization in objective function for open circuit condition	432.3213 to 408.2850	432.3213 to 408.2785

The required time for the estimation process is given in **Table 3**, where consumed time using GA is significantly larger than that of the TRM.

Table 3. Comparison between GA and TRM in term of time-consuming during the estimation process.

Estimation Method	GA	TRM
Time-consuming for short circuit (3%) / Sec	4922	129
Time-consuming for short circuit (10%) / Sec	3704	180
Time-consuming for open circuit / Sec	23004	808

5. CONCLUSION



This paper illustrates the impact of short circuit and open circuit faults on the values of a three-phase induction motor's parameters. The genetic algorithm (GA) and the trust-region method (TRM) are employed to minimize the sum-squared errors between the actual and the corresponding stator currents of the healthy model; the optimization methods' solution is a vector of the estimated basic parameters. The simulation results confirm the following points:

- Both GA and TRM are efficiently converged
- TRM is faster than GA due to the TRM quadratic convergence property
- Under short circuit condition (10% severity), the mutual inductance and rotor resistance are remarkably drifted from their nominal values to lower values
- Under the open-circuit condition, the stator resistance is highly affected and decreased from its nominal value
- The deviation on these basic parameters can be easily adapted for recognizing the open circuit fault from the short circuit fault.

NOMENCLATURE

$\ \cdot \ $	Norm
B_k	Approximate of hessian matrix
g_k	The gradient function
$q_k(\mathbf{d})$	Quadratic function
Δ	Trust-region radius
L_{1r}	Rotor-self inductance
L_{1s}	Stator-self-inductance
L_m	Mutual inductance
r_r	Rotor resistance
r_s	Stator resistance
Subscript \wedge	Referred to estimated values
\mathbf{X}	Vector of design variables
$f(\mathbf{X})$	Objective function
i_{abc}	Instantaneous currents in the three-phases
k	Number of iterations

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