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# A New Method for Identifying Broken Rotor Bars in Squirrel Cage Induction Motor Based on Particle Swarm Optimization Method

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***Abstract***—Detection of squirrel cage induction motor (SCIM) broken bars has long been an important but difficult job in the detection area of motor faults. Early detection of this abnormality in the motor would help to avoid costly breakdowns. A new detection method based on particle swarm optimization (PSO) is presented in this paper. Stator current in an induction motor will be measured and characteristic frequency components of faylted rotor will be detected by minimizing a fitness function using pso. Supply frequency and side band frequencies and their amplitudes can be estimated by the proposed method. The proposed method is applied to a faulty motor with one and two broken bars in different loading condition. Experimental results prove that the proposed method is effective and applicable.

***Keywords***—broken bar; PSO; fault detection; SCIM

## I. Introduction

INDUCTION motor applications are widespread. A majority of the induction motors are used in electric industries, mining industries, petrochemical industries and domestic appliance industries. It is well known that interruptions of a manufacturing process due to a mechanical problem induce a serious financial loss for the firm. Thus, early detection of incipient motor fault is important.

As it is known squirrel-cage induction motors faults can be categorized into electrical and mechanical faults. Electrical faults also can be categorized into stator and rotor faults. Rotor failures are account for 5%-10% of total induction motor failure [1].

Broken rotor bars fault in squirrel-cage induction motors can be detected by monitoring any abnormality of the motor current spectrum amplitudes of several certain frequency components. This is based on the double slip-frequency sidebands of the fundamental supply frequency in the current spectrum [2].

Several monitoring techniques have been developed for broken rotor bar fault detection, most of which are based on motor current signature analysis (MSCA). In recent years advanced signal processing methods based on wavelet transform have been applied to broken rotor bar fault diagnosis [3-5]. Also method based on multiple discriminant analysis (MDA) has been used for diagnosis of broken bars in induction motors [6].

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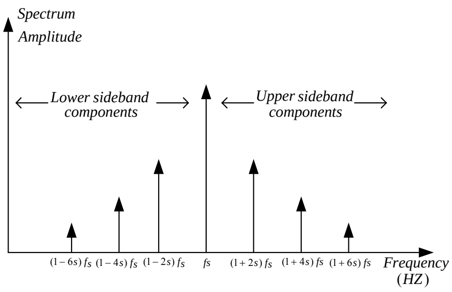



Fig. 1. Sideband frequencies around the fundamental line frequency

This paper describes a new technique for identifying side band harmonics which appears in stator current as a result of broken rotor bars. This method is based on minimizing a fitness function using pso algorithm. The proposed method can identify supply voltage frequency, amplitude of stator current's main harmonic, rotor slip, side band frequency components and their amplitudes. This method is tested on a 1 hp squirrel cage induction motor; both simulation and experimental results confirm the effectiveness of the proposed method.

## II. Broken Rotor Bars in Squirrel- Cage Induction Motors

It is well known when a broken rotor bar fault occurs in IM, sideband components will appear in stator current around the supplied current fundamental frequency:

$$f_{sb} = (1 \pm 2ks) f_s \tag{1}$$

Where
$f_{sb}$ : Sideband frequencies where $f_{sb} > 0 \forall K$
$f_s$ : Supply frequency
$s$ : Slip of the motor
$k$ : 1, 2, 3 …
Sideband frequencies are shown in figure 1.

Figure.1 shows frequency components that appear when an IM faces to a broken bar fault which frequencies are given in (1) for k=1, 2, 3.

Sideband components, shown in figure.1 can be used for broken rotor bar diagnostic process. In the present work, rotor fault detection is investigated using the first lower or upper sidebands around the fundamental supply frequency.

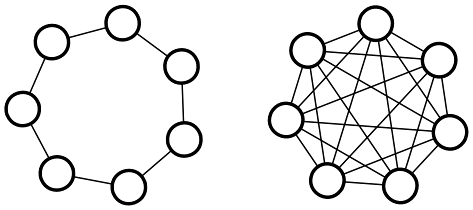
## III. Particle Swarm Optimization

The PSO algorithm was introduced by Eberhart and Kennedy in 1995 [7]. Original PSO was inspired by the behavior of a flock of birds or a school of fish during their food-searching activities. Believed to be effective method in multidimensional, linear and nonlinear problems.

### A. PSO

In PSO algorithm position of each particle corresponds to a candidate solution to the problem. $i^{th}$ Particles moves through the $D$-dimensional search space using a combination of an attraction to the best position that it individually has found, and an attraction to the best position that it's neighbors have found so far. In PSO each particle's neighborhood is defined as the subset of particles which it is able to communicate with. Figure 2 shows the lbest (ring) and gbest (star) topologies. In the lbest topology, each particle is influenced by its immediate neighbors in the population. In the gbest topology, each particle is influenced by entire swarm. In D-dimensional search space the position of $i^{th}$ particle is represented as the vector $\vec{x}_{id} = (x_{i1}, x_{i2}, ..., x_{iD})$ and the velocity of $i^{th}$ particle is represented as the vector $\vec{v}_{id} = (v_{i1}, v_{i2}, ..., v_{iD})$. The best position of $i^{th}$ particle (previous self experience so far) and the best position of entire swarm (experience of swarm so far) are represented as the vector $\vec{p}_i = (p_{i1}, p_{i2}, ..., p_{iD})$ and $\vec{g} = (g_1, g_2, ..., g_D)$. In lbest topology the best position of $i^{th}$ particle's neighbors is represented as the vector $\vec{n}_i = (n_{i1}, n_{i2}, ..., n_{iD})$.

Using the information, In gbest and lbest topologies the algorithm updates velocity of $i^{th}$ particle's $d^{th}$ dimension under the following equations [8].



(a) The ring topology (b) The Star topology

Fig. 2. Particle Swarm topologies

$$v_{id}(t+1) = \omega v_{id}(t) + c_1 rand_1 (p_{id}(t) - x_{id}(t)) + c_2 rand_2 (g_d(t) - x_{id}(t)) \tag{2}$$

Where,

| | |
|---|---|
| $x_{id}(t)$ | current position of $i^{th}$ particle in $d^{th}$ dimension |
| $p_{id}(t)$ | current best position of group in $d^{th}$ dimension |
| $n_{id}(t)$ | current best position of $i^{th}$ particle's neighbors in $d^{th}$ dimension |
| $g_d(t)$ | current best position of group $d^{th}$ dimension |
| $v_{id}(t+1)$ | next velocity of particle i in $d^{th}$ dimension |
| $\omega$ | inertial weight |
| $c_1, c_2$ | Hooke's constants |
| $r_1, r_2$ | random numbers between 0 and 1 |

In velocity equations the $C_1$,$C_2$=2.05 is suggested by [9]. To further accelerates the convergence, a time-varying inertial weight ω is set according to the following equation and varies from $\omega_{max}$=0.9 at the beginning to $\omega_{min}$=0.1 toward the end of the optimization.

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} . iter \tag{3}$$

Where,

| | |
|---|---|
| $iter$ | current iteration number |
| $iter_{\max}$ | maximum iteration number |

Each particle moves from the current position to the next position by the velocity in (2) using the following equation [8]:

$$\vec{x}(t+1) = \vec{x}(t) + \vec{v}(t+1) \tag{4}$$

### B. Fitness Function

To find side band harmonics based on pso algorithm, a fitness function is needed which is depended on supply frequency and motor slip; because these parameters define side band frequencies. It must be mentioned that identification of the nearest components are to fundamental frequency is the base of the diagnostic system. The proposed fitness function for broken bars detection in SCIM is described as follows:

$$\begin{aligned} fitness &= I_s - h_1 \sin(2\pi f_s t + \varphi_1) \\ &- h_{sb1} \sin(2\pi f_{sb1} t + \varphi_{sb1}) - h_{sb2} \sin(2\pi f_{sb2} t + \varphi_{sb2}) \\ f_{sb1} &= (1-2s) f_s \\ f_{sb2} &= (1+2s) f_s \end{aligned} \tag{5}$$

Where,

$I_s$ : Stator current

$f_s$ : Supply frequency

$s$ : Motor slip

$f_{sb1}$ : Lower side band frequency due to broken bar

$f_{sb2}$ : Upper side band frequency due to broken bar

$h_1, h_{sb1}, h_{sb2}$ : Amplitude of harmonic components

$\varphi_1, \varphi_{sb1}, \varphi_{sb2}$ : Initial phase of harmonic components

In the fitness function, stator current is obtained from sampling of one phase of real SCIM or simulated motor; other parameters must be identified using PSO.

Sideband harmonics also exist in healthy motors. Although their amplitudes are small, they can be identified by the pso, which implies a faulty diagnosis; thus a non zero limit must be selected for searching the components in pso algorithm. This limit differs in SCIMs proportional to their power. In 1 hp SCIM which is investigated in this paper, side band frequencies are less than .001A when motor is healthy; thus search space is in [0.0001 0.05].

Motor slip in full load condition is 5%, considering 20% overloading span of motor slip become in [0.0001 0.06]. Fundamental component of stator current is equal to peak value of the stator current approximately. Initial phase of harmonic components are depended to stator current window, so it varies between $-\pi$ and $\pi$ . Also supply frequency doesn't have a constant value and varies from 49.7 Hz to 50.3 Hz in Iran.

Becoming specified the parameters' search spaces, fitness function can be minimized by PSO. If search algorithm finds a reliable value for side bands' amplitude, it means that motor is faulty and at least one broken bar exists in rotor.

## IV. SIMULATION AND EXPERIMENTAL RESULTS

Winding function is used for simulating SCIM. In order to enhance the accuracy of simulation, real distribution of stator winding and rotor bars are used for modeling the motor [10]. Steady state of stator currents with their spectrum for 1 hp motor with broken bars are shown in figure 3 and 4.

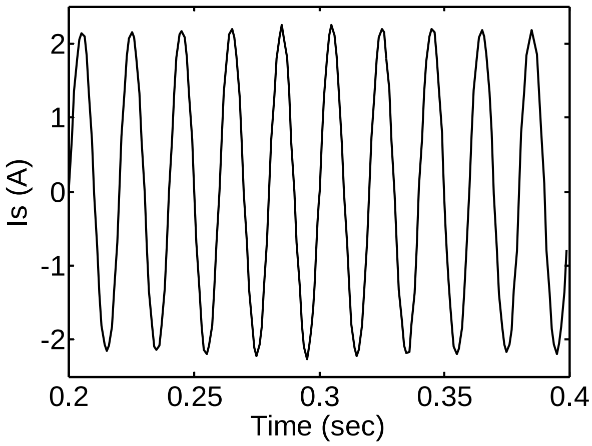



Fig. 3 . (a)

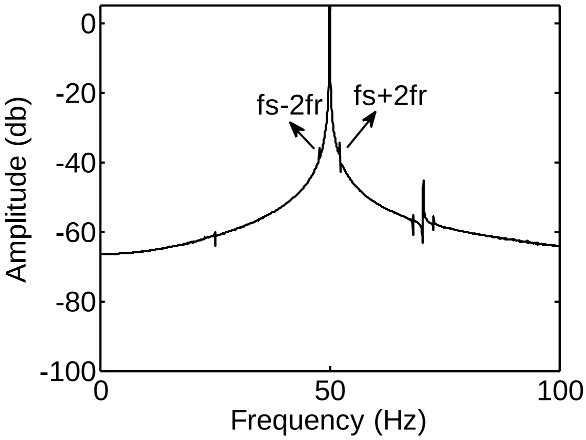



Fig. 3. (b)

Fig. 3 . (a) Stator current, (b) Spectrum of stator current; 50% loading with 1 broken bar

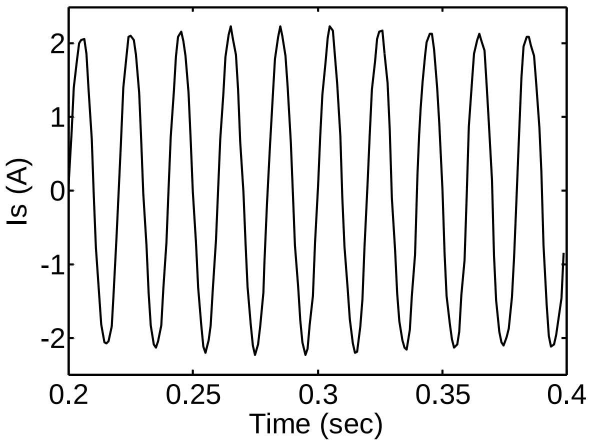



Fig. 4. (a)

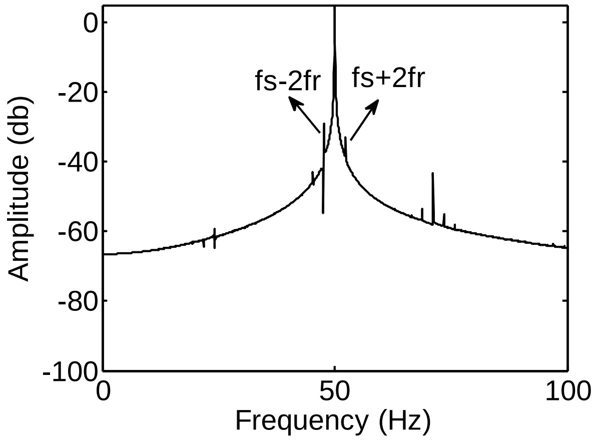



Fig. 4. (b)

Fig. 4 . (a) Stator current, (b) Spectrum of stator current; 50% loading with 2 broken bar

In order to test the proposed method with stator currents of a real motor, we built a test bench for measurements which contains a coupled SCIM and DC generator of a power 1 hp. Also a variable resistance is used for applying different loading to the motor. Test bench is shown in figure 5.

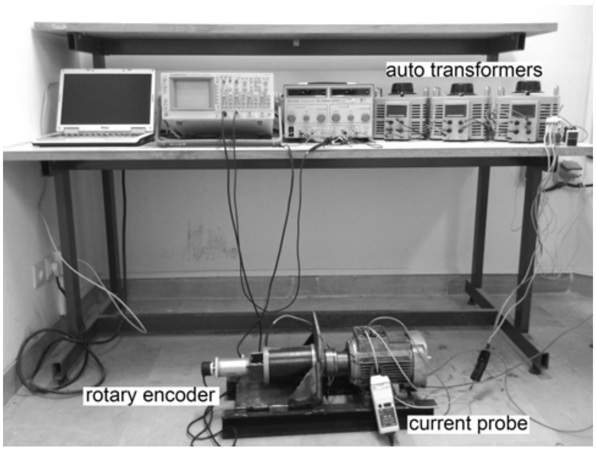



Fig. 5 .Test bench of induction motor

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Motor is tested with one broken bar and two broken bars under 25%, 50% loading and no load condition. Steady state of stator currents for the real motor under broken bars fault are shown in figure 6 and 7.

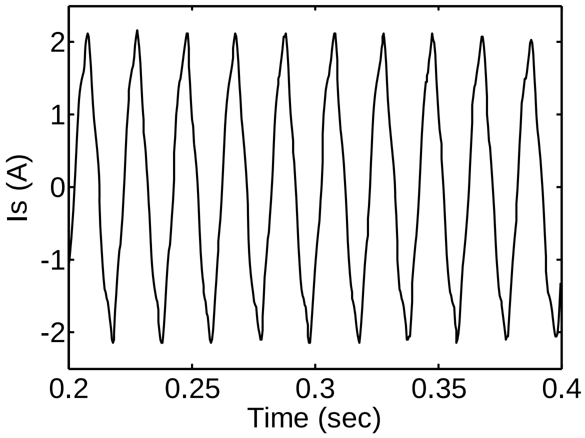

Fig. 6 . (a)

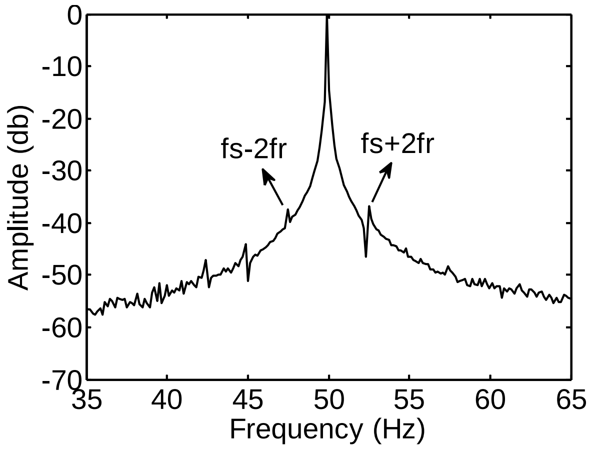

Fig. 6 . (b)

Fig. 6 . (a) Stator current, (b) Spectrum of stator current; 50% loading with 1 broken bar [experimental results]

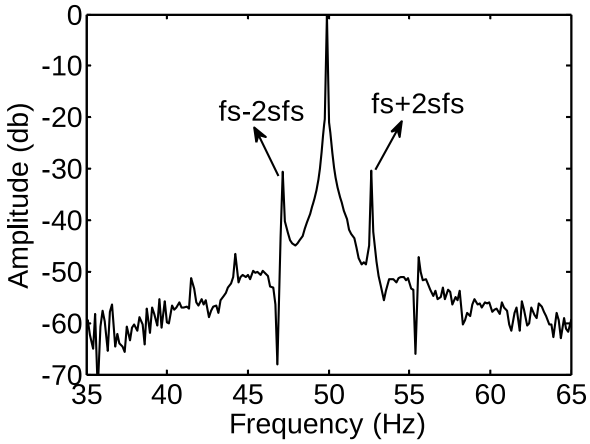

Fig. 7 . (a)

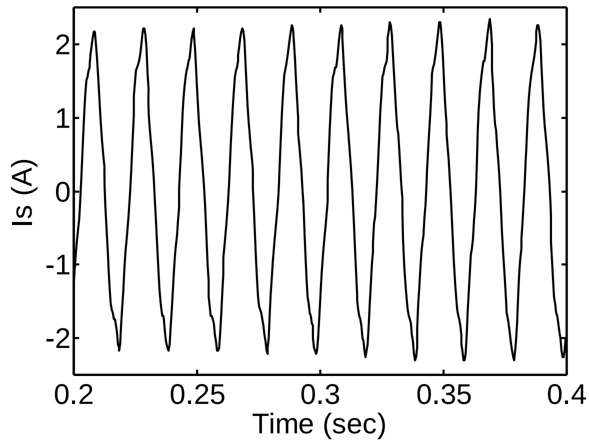

Fig. 7 . (b)

Fig. 7 . (a) Stator current, (b) Spectrum of stator current; 50% loading with 2 broken bar [experimental results]

Having stator currents and minimizing the fitness function, side band components will be identified, thus broken bars will be detected. Figure 8 shows convergence of the fitness function when two bars of the rotor are broken and motor is loaded 50%.

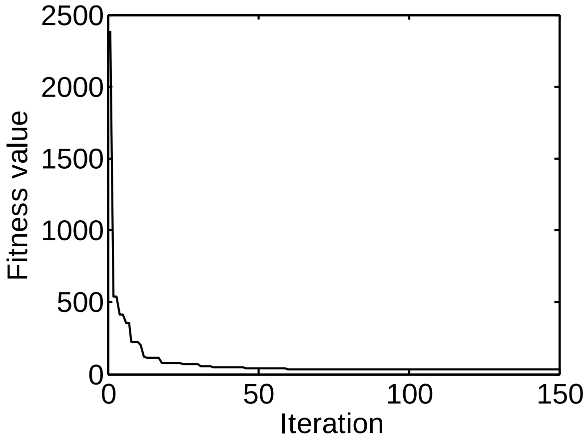

Fig. 8 .Convergence of fitness function

Supply frequency and motor slip convergences for the above-mentioned case are shown in figures 9 and 10 respectively.

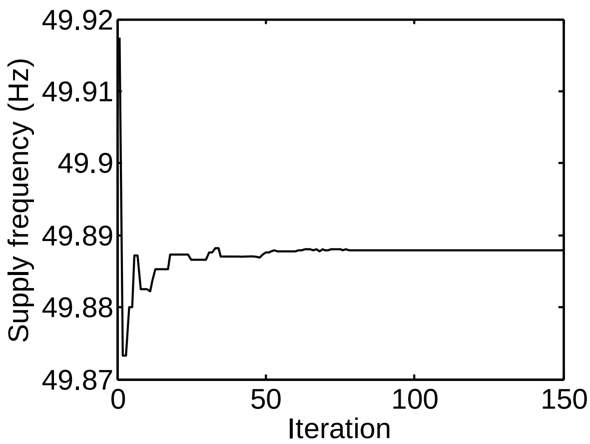

Fig. 9.Supply frequency convergence

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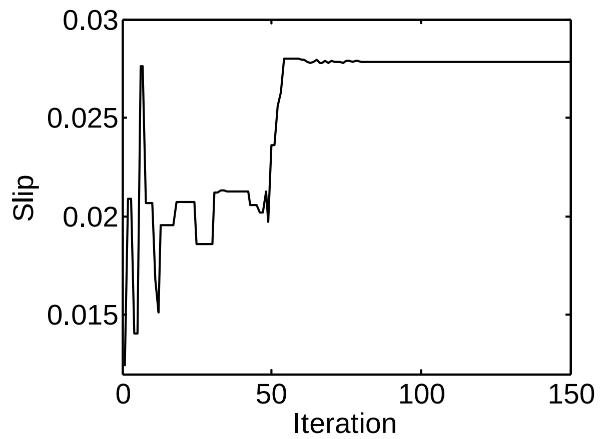


Fig. 10. Motor slip convergence

Harmonic components identification results for faulty and healthy motor for both simulation and experimental results are shown in Table I and II respectively.

TABLE I SIMULATION RESULTS FOR 1 HP MOTOR UNDER DIFFERENT LOADING CONDITION

| Motor state | | loading | $h_{sb1}$ | $h_{sb2}$ | s | $f_s$ |
|---|---|---|---|---|---|---|
| faulty | one broken bar | No load | .0015 | .0022 | .0105 | 50 |
| | | 25% | .0040 | .0052 | .0191 | 50 |
| | | 50% | .0053 | .0074 | .0324 | 50 |
| | two broken bars | No load | .0029 | .0039 | .0168 | 50 |
| | | 25% | .0038 | .0052 | .0321 | 50 |
| | | 50% | .0062 | .0079 | .0375 | 50 |
| healthy | | No load | ≈ 0 | ≈ 0 | .0120 | 50 |
| | | 25% | .0002 | .0003 | .0301 | 50 |
| | | 50% | .0002 | .0005 | .0464 | 50 |

TABLE II EXPERIMENTAL RESULTS FOR 1 HP MOTOR UNDER DIFFERENT LOADING CONDITION

| Motor state | | loading | $h_{sb1}$ | $h_{sb2}$ | s | $f_s$ |
|---|---|---|---|---|---|---|
| faulty | one broken bar | No load | .0021 | .0028 | .0165 | 50.03 |
| | | 25% | .0036 | .0049 | .0211 | 49.92 |
| | | 50% | .0049 | .0069 | .0264 | 50.08 |
| | two broken bars | No load | .0027 | .0031 | .0178 | 50.04 |
| | | 25% | .0042 | .0058 | .0261 | 49.96 |
| | | 50% | .0058 | .0073 | .0275 | 49.88 |
| healthy | | No load | ≈ 0 | ≈ 0 | .0161 | 50.06 |
| | | 25% | .0003 | .0005 | .0221 | 50.01 |
| | | 50% | .0004 | .0006 | .0264 | 49.98 |

## V. CONCLUSION

In this paper a very simple method for broken rotor bars based on PSO algorithm was proposed. A fault detection criterion is existence of side band harmonics. This method doesn't need complicated and huge computational process. Also proposed method doesn't require advanced measuring equipments; only a current sensor was used for sampling one phase of stator current. The proposed method was tested on 1 hp induction motor under different loading condition. Both simulation and experimental results showed effectiveness of the proposed method.

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