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Application of Particle Swarm Optimization to PMSM Stator Fault Diagnosis

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***Abstract*— Permanent Magnet Synchronous Motors (PMSM) are frequently used to high performance applications. Accurate diagnosis of incipient faults can significantly improve system availability and reliability. This paper proposes a new scheme for the automatic diagnosis of turn-to-turn short circuit faults in PMSM stator windings. Both the fault location and fault severity are diagnosed using a particle swarm optimization (PSO) algorithm. The performance of the motor under the fault conditions is simulated through lumped-parameter models. Waveforms of the machine phase currents are monitored, based on which a fitness function is formulated and PSO is used to identify the fault location and fault size. Simulation results in MATLAB provide preliminary verification of the diagnosis scheme.**

I. INTRODUCTION

RELIABILITY, survivability, availability and other related issues are becoming major concerns in the development of most advanced systems and processes [1]. With the advancement of permanent magnet materials, permanent magnet synchronous motors (PMSM) are receiving increasing attention for high efficiency and high performance applications [2]. Efficient online condition monitoring and accurate machine fault diagnosis are thus becoming significant in various industrial applications and also hot research topics. Much work reported in the literature on fault diagnosis of electric machines is focused on induction motors, e.g. [3]-[5] and the references therein. However, the research on PM motor diagnosis is gathering its speed as more and more PM motors are considered for high performance applications, such as electric vehicles and ship propulsion systems.

After continuous operation under severe circumstances, PMSM are inclined to certain fault conditions. The most common fault modes are categorized into two types, i.e. mechanical faults and electrical ones. Statistics show that the stator winding faults constitute the largest portion of the electrical faults [6][7]. The turn-to-turn fault of motor windings usually starts as an undetected insulation failure between two adjacent turns, and then develops into a short circuit isolating a number of turns [8][9]. The winding faults in a single stator coil may have relatively little effect on motor performance but may affect overall motor reliability, availability, and longevity [10]. Efficient diagnosis of the stator winding faults together with timely maintenances can significantly improve system reliability and availability. Recently several papers are published on the stator winding fault diagnosis of PM motors. For instance, Nelson and Chow presented their work on a prototype axial flux variable reluctance (VR) PM motor in [10], where the motor is constructed to imitate various stator winding fault conditions. Diagnosis of stator winding faults of a CSI-fed PM brushless DC motor is investigated in [11] with the neuro-fuzzy method. While the detection of PMSM stator turn-to-turn fault can be accomplished with several methods, such as negative sequence components analysis [12], vibration analysis [13], etc., not much publication is available on the accurate identification of fault location and fault severity represented by the number of shorted turns after the detection of the fault. However, this accurate fault diagnosis directly facilitates the timely maintenance, avoids catastrophic failures, and thus improves system reliability and availability significantly. For military applications, a reduced-rating, fight-through capacity may be possible.

The present work introduces a new perspective for the stator winding fault diagnosis of PMSM motors using the particle swarm optimization (PSO) approach. A generalized lumped parameter model is utilized to simulate the motor performance under both healthy and fault conditions. Under the stator winding fault condition, two parameters are introduced into the model: One is continuous variable representing the size of the fault. It is defined as the percentage of the shorted turns among the total turn numbers. The other, representing the fault location, takes the angle difference between the three phases and phase *a,* which is a discrete variable (0, $2/3\pi$, and $-2/3\pi$ only). These two variables need to be identified simultaneously in order to diagnose both the fault location and fault size. As the model of the PMSM under stator fault condition is asymmetrical and highly nonlinear, the parameter identification problem becomes a "nonlinear in its inputs" (non-LI) and "nonlinear in its parameters" (non-LP) model structure as defined in [14]. The traditional parameter identification approaches, e.g. least-squared algorithms based on quadratic error functions, either do not apply or do not guarantee a global solution. As an evolutionary computation (EC) technique developed in mid 1990s, the PSO approach exhibits many advantages for complex engineering problems. This paper uses the PSO method for the automatic fault diagnosis of PMSM stator

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winding faults.

The paper is organized as follows. The generalized lumped parameter model of the PMSM under fault conditions is briefly introduced in Section II, and then the diagnosis of the stator winding fault diagnosis is put forward as a general parameter identification problem. Section III provides a brief overview of the PSO method and its state-of-art development. The diagnosis problem described in section II is then reformulated into a mixed-variable PSO optimization problem in section IV, and the algorithm is described in the same section. Simulation results are given in section V showing the effectiveness of the method. Conclusions are made in section VI.

II. PMSM Fault Modeling and Problem Formulation

PMSM dynamics under both healthy and faulty operations can be simulated with lumped parameter models based on coupled magnetic circuit principle [15]. Modeling of the healthy PMSM with balanced three-phase input has been widely recognized, which are generally expressed in *dq*-axis rotor reference frame by applying Park transformation [15][16]. This section focuses on the introduction of PMSM modeling under stator turn-to-turn short in one of its phase windings. This model directly serves the fault diagnosis purposes.

Fig. 1 shows the faulty PMSM magnetic circuit model, where a partial turn-to-turn short is illustrated in the stator winding of phase *b*. In order to take into account the presence of the shorted circuit in the PMSM model, we need to partition the affected phase windings and include an extra circuit for that phase. This extra circuit creates a stationary magnetic field, which modifies the original field by adding the fourth coupled magnetic circuit into the system. To clearly represent the fault size and its location, two new parameters, σ and θ_f, are introduced. σ denotes the fault size, which is defined as the ratio of the shorted turns (N_f) to the total turn number N_s. θ_f is a fault location parameter, which is the angle between the faulted phase and the phase *a* axis. Hence, θ_f can only take three different values, 0, 2π/3 or -2π/3, corresponding to a stator winding fault in *a*, *b*, or *c* phase respectively. Defining the electrical quantities of the new circuit with the subscript "*f*" (fault), we obtain the motor voltage equation in matrix format as (1).

$$\begin{aligned} v^s_{abcf} &= r^s_{abcf} i^s_{abcf} + L_s \frac{di^s_{abcf}}{dt} + \frac{d\Psi_{mabcf}}{dt}, \quad \text{where} \\ v^s_{abcf} &= \begin{bmatrix} v^s_a & v^s_b & v^s_c & v^s_f \end{bmatrix}^T, \; v^s_f = 0 \\ i^s_{abcf} &= \begin{bmatrix} i^s_a & i^s_b & i^s_c & i^s_f \end{bmatrix}^T \\ \Psi_{mabcf} &= \begin{bmatrix} \Psi_{ma} & \Psi_{mb} & \Psi_{mc} & \Psi_{mf} \end{bmatrix}^T \end{aligned} \tag{1}$$

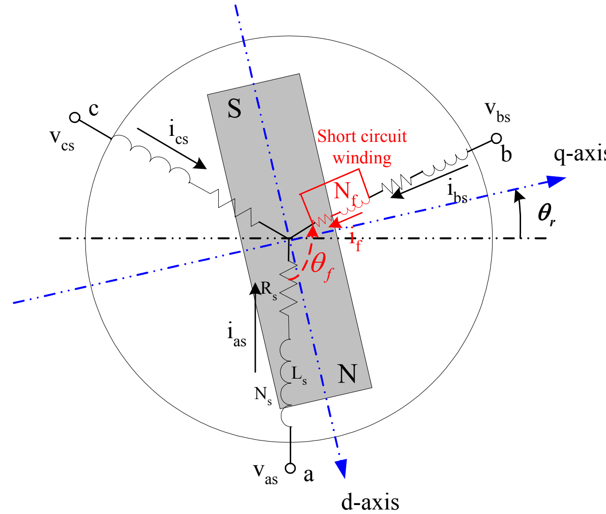

Fig. 1. PMSM circuit model with stator winding short

In (1), symbols v^s, r^s, i^s and Ψ denote stator quantities, i.e. voltages, resistances, currents and PM magnetic fluxes, respectively, in *abc*-phases and the faulted circuit. The PM flux linkage in the fault phase is partitioned into two parts, i.e. Ψ_{mb} and Ψ_{mf}, proportional to fault size parameter σ. Including the fault location parameter θ_f, the PM magnetic fluxes can be expressed as periodic functions of rotor position, θ_r, using the magnitude of the permanent magnet flux linkage constant Ψ_m.

$$\Psi_{mabcf} = \begin{bmatrix} \Psi_{ma}(\theta_r,\theta_f) \\ \Psi_{mb}(\theta_r,\theta_f) \\ \Psi_{mc}(\theta_r,\theta_f) \\ \Psi_{mf}(\theta_r,\theta_f) \end{bmatrix} = \Psi_m \begin{bmatrix} \sin(\theta_r - \theta_f) \\ (1-\sigma)\sin(\theta_r - 2\pi/3 - \theta_f) \\ \sin(\theta_r + 2\pi/3 - \theta_f) \\ \sigma \sin(\theta_r - 2\pi/3 - \theta_f) \end{bmatrix} \tag{2}$$

Under the fault condition, the matrices, r^s and L_s, become functions of σ and θ_f. For a fault in phase *b*, the resistance r^s can be expressed in (3).

$$r^s_{abcf} = \begin{bmatrix} r^s_a & 0 & 0 & 0 \\ 0 & (1-\sigma)r^s_b & 0 & 0 \\ 0 & 0 & r^s_c & 0 \\ 0 & 0 & 0 & \sigma r^s_f \end{bmatrix} \tag{3}$$

The calculation of L_s is much more involved. Its simplified expression is given in (4), which is only an illustrative example with the inductance leakage neglected. More accurate calculation of L_s is discussed in [17] and the references therein.

$$L_s = \begin{bmatrix} L & (1-\sigma)M & M & \sigma M \\ (1-\sigma)M & (1-\sigma)^2 L & (1-\sigma)M & (1-\sigma)\sigma L \\ M & (1-\sigma)M & L & \sigma M \\ \sigma M & (1-\sigma)\sigma M & \sigma M & \sigma^2 L \end{bmatrix} \tag{4}$$

L and *M* in (4) are inductance constants.

The electrical angular velocity ω_r and the angular position θ_r are needed to obtain the numerical solution of the motor electrical quantities. Thus, we must incorporate the transient mechanical model of the PMSM. According to Newton's law, we have the mechanical model (5) and (6).

$$\frac{d\left(\omega_r/n_p\right)}{dt} = \frac{1}{J}\left[T_e - B_m\left(\omega_r/n_p\right) - T_L\right] \tag{5}$$

$$\frac{d\theta_r}{dt} = \omega_r \tag{6}$$

In (5), n_p is the number of pole pairs of the motor; J denotes the inertia of the rotor; B_m is the viscous friction coefficient; T_e is the electromagnetic torque and T_L is the load torque. According to [16], T_e can be derived from the coenergy of the magnetic system, W_c, as in (7).

$$T_e = n_p \frac{\partial W_c}{\partial \theta_r}, \text{ with}$$
$$W_c = \frac{1}{2}\left(i^s_{abc}\right)^T L_s \left(i^s_{abc}\right) + \left(i^s_{abc}\right)^T \Psi_{mabc} + W_{PM} \tag{7}$$

W_{PM} is a constant representing the energy stored in the permanent magnet. The PMSM transient response can now be obtained by solving the differential equations (1)-(7).

Comprehensive diagnosis implies fault detection, faulty location, and identification of fault severity (size). As applied to our problem, the detection can be achieved by comparing motor performances under healthy and faulty conditions and analyzing the discrepancies of electrical or mechanical quantities with signal processing tools, such as FFT, e.g. [3][5][10]. However, locating and identifying the fault are not always possible through this process. With a proper fault model at hand, this process can be simply viewed as a parameter identification problem with measured data, which can be solved by minimizing certain cost functions representing estimation errors. However, a further look at the PMSM model indicates that the commonly used identification approaches are not applicable to this non-LI non-LP model structure. The approach presented in next section provides a solution.

III. Overview of Particle Swarm Optimization [18][19][20]

This section provides an overview of the particle swarm optimization method together with its state-of-art development.

PSO is one of the population-based evolutionary computation techniques, where the population is called *swarm*, and each member of the swarm is called *particle*. PSO algorithm was first introduced by Kennedy and Eberhart in 1995 [18] and has been used to solve a broad range of optimization problems. The algorithm was discovered through simulating the animals' social activities, e.g. insects, birds, etc. It attempts to mimic the natural process of group communication to share individual knowledge when such swarms flock, migrate, or hunt. Starting with a randomly initialized population, each particle in PSO *flies* through the searching space with a dynamically adjusted velocity. The velocity adjustment is based upon the historical behaviors of the particles themselves as well as their companions'. In this way, the particles tend to *fly* towards better and better searching areas over the searching process [19][23]. The searching procedure based on this concept can be described by (8).

$$v_i^{k+1} = w_i v_i^k + c_1 rand_1 \times \left(pbest_i - x_i^k\right) + c_2 rand_2 \times \left(gbest - x_i^k\right) \tag{8a}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{8b}$$

In (8), c_1 and c_2 are positive constants, defined as acceleration coefficients; w_i is the inertia weight factor; $rand_1$ and $rand_2$ are two random functions in the range of [0,1]; x_i represents the i^{th} particle and $pbest_i$ the best previous position of x_i; *gbest* is the best particle among the entire population; v_i is the rate of the position change (velocity) for particle x_i. Velocity changes in (8a) comprise three parts, i.e. the momentum part, the "cognitive" part, and the "social" part. This combination provides a velocity getting closer to *pbest* and *gbest*. Every particle's current position is then evolved according to (8b), which produces a better position in the solution space. Fig. 2 is a conceptual illustration of this searching process.

The implementation procedure of the PSO algorithm can be illustrated with the flowchart in Fig. 3. The optimization process begins with a random initialization. For each generation of particles, the fitness is evaluated to find the local best (*pbest*) and the global best (*gbest*). The particles' new velocities and positions are then calculated according to (8). The process is repeated until reaching the desired fitness value corresponding to certain generation number.

After its emergence, the PSO has been improved from various perspectives, including algorithm, topology, parameters, etc. A number of variations are developed to serve different needs. One extension is the modified PSO to tackle discrete variables problems [21][22]. In [23], a mixed integer nonlinear (MINLP) optimization problem is solved with the proposed PSO and applied to reactive power and voltage control considering voltage security assessment. The modified PSO for MINLP problem is illustrated in Fig. 4, where the discrete variables use grids instead of continuous axis for their positions and velocities. In this way, consistency is maintained for solving the continuous and discrete variable problems using PSO.

IV. PSO Approach for Diagnosis of PMSM stator Fault

By simplicity in concept, PSO has been successfully

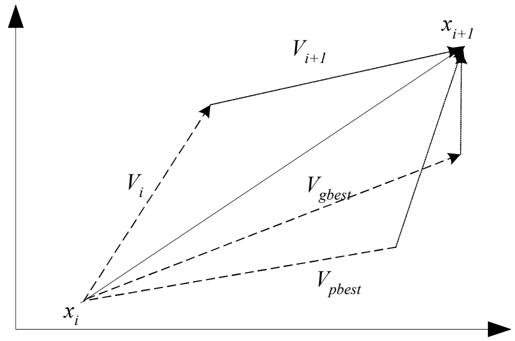

Fig. 2 Conceptual illustration of searching process [23]

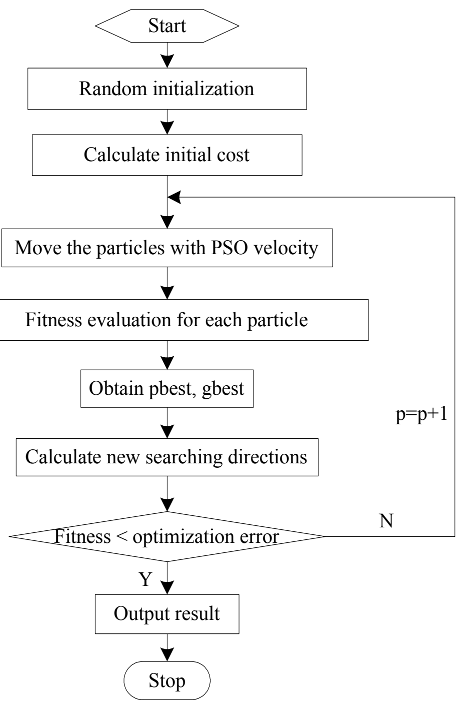

Fig. 3. Flowchart of the PSO Algorithm

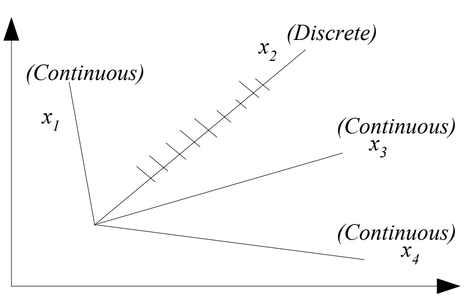

Fig. 4 Concept for modified PSO for MINLP [23]

utilized to solve many practical engineering problems. It is especially suitable for those nonlinear or stochastic systems in nature, where analytic search and linear programming cannot apply.

As described in Section II, the diagnosis of the PMSM stator winding fault can be considered as an non-LI non-LP parameter identification problem, where two parameters, σ (fault size) and θ_f(fault location), need to be identified. The structure of the proposed identification approach using PSO is illustrated in Fig. 5. A database is utilized here instead of repeatedly running the fault model during the evaluation of PSO fitness for all the populations. The use of database significantly increases the speed of the diagnosis process. Considering the convenient measurement of the motor phase currents, we take the differences between the measured currents and their simulated counterparts from the fault model to form the fitness function to be optimized. A normalized quadratic function as described in (7) is chosen in our investigation.

$$J\left(\sigma,\theta_f\right)=\sum_t\left[\begin{array}{r}\left(\dfrac{\left(i_a(t)-\hat{i}_a(t)\right)}{mag\left(i_a(t)\right)}\right)^2+\left(\dfrac{\left(i_b(t)-\hat{i}_b(t)\right)}{mag\left(i_b(t)\right)}\right)^2+\\ \left(\dfrac{\left(i_c(t)-\hat{i}_c(t)\right)}{mag\left(i_c(t)\right)}\right)^2\end{array}\right] \quad (7)$$

In (7), i_{abc} is the actual current measurement, and $\hat{i}_{abc}$ is simulated and recalled from the database. The symbol "*mag*" denotes the magnitude of the corresponding phase currents. The PSO algorithm in Fig. 3 is then performed repetitively until reaching the desired error limit.

V. SIMULATION

A three phase PMSM with non-salient poles is simulated in MATLAB® to demonstrate the performance of the PSO approach for the diagnosis of the stator winding fault. The nominal parameters of the simulated PMSM are summarized in Table I.

To begin with, simulations are performed for the motor operations under the turn-to-turn short fault with different severity in each of the phase windings, and a diagnostic database is built accordingly. The database is composed of the measurable outputs during the motor monitoring, which is here the stator currents, with the fault size and fault location angle as the indices. The size of the database depends on the index data density. Increasing this density provides a better accuracy during the estimation of the fault severity, however, it requires larger storage spaces. Thus, there is a tradeoff. In this work, linear interpolation is used to improve the diagnosis accuracy with a database of reasonable size.

To examine the performance of the PSO approach for fault location and fault size identification, a 4.5% turn-to-turn fault is applied to stator phase winding *b* at $t=3sec$. The post-fault current of the PMSM is displayed in Fig. 6, where originally balanced three-phase current becomes slightly unbalanced under this relatively small fault. The diagnosis is then performed using the PSO algorithm. Fig. 7 shows the fitness function variation with the generation numbers during the optimization process. With eight particles in each generation, the PSO converges to its *optimum* with sufficiently small error within *25* generations. The straight line in Fig. 8 indicates that the fault location parameter θ_f can usually be identified in one or two generations in most of the runs. The estimation of fault size σ takes more effort. The plot of the fault size versus generation numbers is given in Fig. 9, which well correspond to the fitness function plot in Fig. 7. The final estimation error is less than ±*0.5%*. Once the database is built properly, the whole PSO diagnostic process can be completed quickly, on the order of seconds.

VI. Conclusions

This paper proposed a new diagnostic method for PMSM stator winding fault. The diagnosis is performed using a particle swarm optimization technique based on stator current monitoring. Both fault location and fault severity are taken into account. Once the appropriate database is built based upon the transient model of PMSM under fault conditions, the PSO diagnostic approach provides fast and accurate diagnosis results. Accurate and timely diagnosis of the incipient fault of the PMSM significantly improves system availability and reliability as maintenance can be scheduled before the faults developing into catastrophic failures. The performance of the proposed approach is demonstrated with MATLAB simulations. For further verification, experimental study is to be performed in the future.

References

[1] L. Liu, K. P. Logan, and D. A. Cartes, “Fault Detection, Diagnosis and Prognostics: Software Agent Solutions”, 1st IEEE Symposium on Electric Ship Technology (ESTS), 26-27 Jul. 2005.

[2] M. A. Rahman and P. Zhou, “Analysis of brushless permanent magnet synchronous motors”, IEEE Trans. Industrial Electronics, vol. 43, no. 2, pp. 256–267, 1996.

[3] F. Filippetti, G. Franceschini, C. Tassoni, and P. Vas, “Recent developments of induction motor drives fault diagnosis using AI techniques”, IEEE Trans. Industrial Electronics, vol. 47, no. 5, pp. 994–1004, Oct. 2000.

[4] S. M. A.Cruz, A. J. M. Cardoso, “Multiple Reference Frames Theory: A New Method for the Diagnosis of Stator Faults in Three-Phase Induction Motors”, IEEE Trans. Energy Conversion, vol. 20, no. 3, pp. 611–619, Sept. 2005.

[5] S. M. A. Cruz, and A. J. M Cardoso, “Diagnosis of stator inter-turn short circuits in DTC induction motor drives”, IEEE Trans. Ind. Applicat., vol. 40, Issue 5, pp. 1349–1360, 2004.

[6] O. Ojo, O. Osaloni, and P. Kshirsagar, “Models for the control and simulation of synchronous type machine drives under various fault conditions”, in 2002 Conference Record Ind. Applicat. Conference, 37th IAS Annual Meeting, vol. 3, pp. 1533– 1540.

[7] P. F. Allbrecht, J. C. Appiarius, and R. M. McCoy, et al, “Assessment of the reliability of motors in utility applications – updated”, IEEE Trans. Energy Conversion, vol. 1, no. 1, pp. 39-46, 1986.

[8] M. A. Awadallah, and M. M.Morcos, “ANFIS-based diagnosis and location of stator interturn faults in PM brushless DC motors”, IEEE Trans. Energy Conversion, vol. 19, no. 4, pp. 795–796, 2004.

[9] J. Penman, H. G. Sedding, B. A. Lloyd, and W. T. Fink, “Detection and location of interturn short circuits in the stator windings of operating motors”, IEEE Trans. Energy Conversion, vol. 9, no. 4, pp. 652–658, 1994.

[10] A. L Nelson, and M. Y. Chow, “Characterization of coil faults in an axial flux variable reluctance PM motor”, IEEE Trans. Energy Conversion, vol. 17, no. 3, pp. 340–348, 2002.

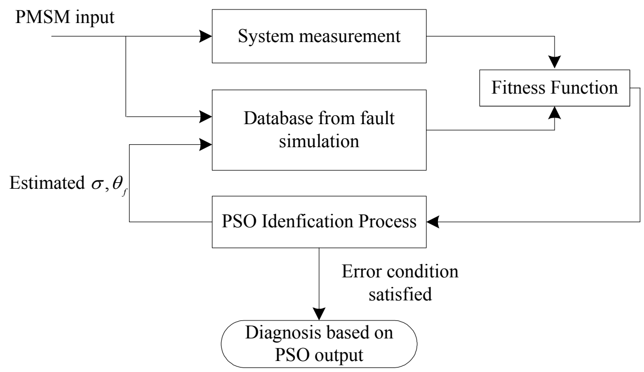

Fig. 5 Block diagram of the PSO idenfication approach

TABLE I
PMSM Parameters

PMSM parameters	Nominal values (*unit*)
Pole pairs n_p	1
Stator resistance r_s	1.4 (Ω)
q-axis inductance L_q	7.3 (*mH*)
d-axis inductance L_d	7.3 (*mH*)
PM flux linkage ψ_m	0.1546 (*Wb-turn*)
Frictional coefficient B_m	0.01 (*N.m/rad/sec*)
Moment of inertia J	0.006 ($kg.m^2$)

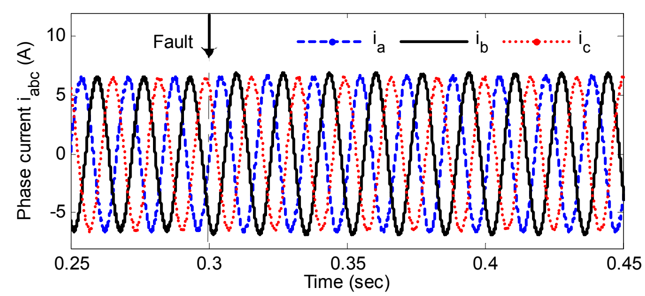

Fig. 6 PMSM phase current under a *4.5%* stator fault in phase *b*

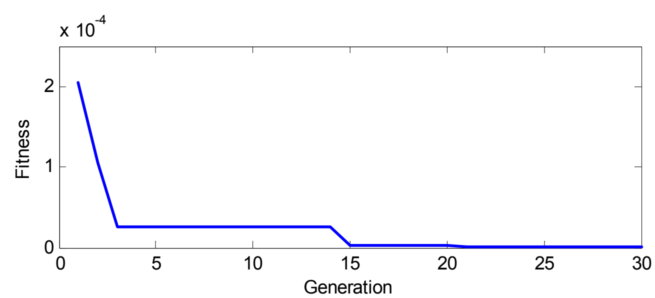

Fig. 7 Optimization of fitness function during a *4.5%* stator fault in phase *b*

[11] M. A. Awadallah, M. M. Morcos, S. Gopalakrishnan, and T. W. Nehl, “A Neuro-Fuzzy Approach to Automatic Diagnosis and Location of Stator Inter-Turn Faults in CSI-Fed PM Brushless DC Motors”, IEEE Trans. Energy Conversion, vol. 20, no. 2, pp. 253–259, 2005.

[12] R. McCann, “Detection and optimal compensation of unbalanced AC motor drives using DISC analysis”, 4th IEEE International Symposium

on Diagnostics for Electric Machines, Power Electronics and Drives (SDEMPED), pp. 334–337, 24-26 Aug. 2003.
[13] F. C. Trutt, J. Sottile, J. L Kohler, "Detection of AC machine winding deterioration using electrically excited vibrations", IEEE Trans. Ind. Applicat., vol. 37, no. 1, pp. 10–14, 2001.
[14] E. Walter and L. Pronzato, Identification of Parametric Models from Experimental Data, Masson, UK: Springer, 1997.
[15] P. C. Krause, and O. Wasynczuk, Electromechanical Motion Devices, McGraw-Hill, 1989.
[16] S. E. Lyshevski, Electromechanical Systems, Electric Machines, and Applied Mechatronics, CRC Press LLC, 2000, ch. 7.
[17] L. Liu, and D. A. Cartes, "Asymmetrical PMSM Modeling for the Purpose of Fault Diagnosis", submitted for publication.
[18] J. Kennedy, and R. Eberhart, "Particle Swarm Optimization", Proceedings of IEEE International Conference on Neural Networks, vol. 4, pp. 1942-1948, Perth, Australia, 1995.
[19] Y. Shi, "Particle Swarm Optimization", Feature article, Electronic Data Systems, Inc., IEEE Neural Networks Society, Feb. 2004.
[20] J. Kennedy, R. C. Eberhart, and Y. Shi, Swarm Intelligence, San Francisco: Morgan Kaufmann Publishers, 2001.
[21] J. Kennedy, and R. C. Eberhart, "A discrete binary version of the particle swarm algorithm," Proceedings of the World Multiconference on Systemics,Cybernetics and Informatics, pp. 4104-4109, 1997.
[22] C. K. Mohan, and B. Al-kazemi, "Discrete particle swarm optimization," Proceedings of the Workshop on Particle Swarm Optimization, 2001.
[23] H. Yoshida, K. Kawata, Y. Fukuyama, S. Takayama, and Y. Nakanishi, "A particle swarm optimization for reactive power and voltage control considering voltage security assessment", IEEE Trans. Power Systems, vol. 15, no. 4, pp. 1232 – 1239, Nov. 2001.

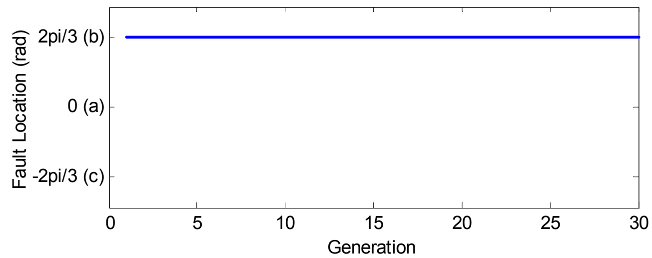

Fig. 8 Fault location estimation during a *4.5%* stator fault in phase *b*

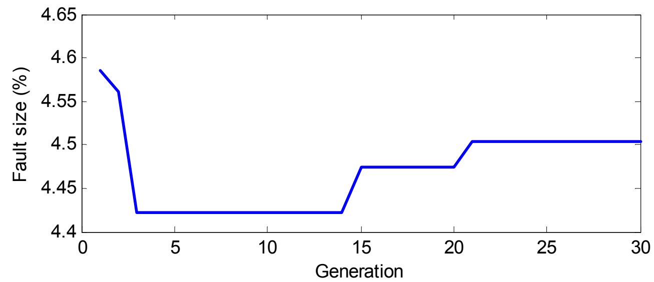

Fig. 9 Fault severity estimation during a *4.5%* stator fault in phase *b*