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COMPARISON IN THE APPLICATION OF GENETIC ALGORITHM AND PARTICLE SWARM OPTIMIZATION IN UNBALANCE IDENTIFICATION IN ROTATING MACHINERY

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Abstract. *The investigation of rotating machinery faults occupies an outstanding position in rotor dynamic field. The most common fault in rotating system is the mass unbalance. Several identification methods were applied to identify the unbalance amplitude, phase angle and axial position. Robust optimization methods can be applied to avoid local minimum in the optimization process used in the unbalance parameter identification. Because of that, meta-heuristics search methods are interesting tools for solving this problem. This work proposes a comparison of the performance of the Genetic Algorithm (GA) and the Particle Swarm Optimization (PSO). The PSO is a population based stochastic optimization technique inspired by the social behavior of bird flocking or fish schooling. The potential solutions, called particles, "fly" through the problem space by following the current optimum particles, allowing the process to find the global optimum solution through this migration. On the other hand, the GA is based on an evolution process. In this case the potential solutions are represented by individuals that belong to a population (set of solutions). This population generates a new population through the evolution operators. The finite element method is used to model the rotating system, and the analysis is carried out in the frequency domain through the unbalance response. The journal bearings stiffness and damping coefficients were previously identified by a model updating process, and they are included in the system model. The experimental set up consists of a rotor, supported by two cylindrical journal bearings on a rigid foundation. The convergence of the processes is also analyzed, taking into account the mean and the standard deviation of the objective function, regarding the unbalanced mass identification convergence in both search methods.*

Keywords: *unbalanced identification, rotating system, genetic algorithm, particle swarm optimization.*

1. INTRODUCTION

The study of rotating machines is an important research topic in machines dynamics field, in view of the significant operational phenomena related to these machines. Mathematical models are developed to foresee the dynamic behavior of rotor-bearing systems, so that, faults that cause vibration in the system can be identified. One of the most common sources of vibration in rotating machines is the mass unbalance. Several model-based fault identification methods were developed to identify the mass unbalance parameters, considering the difference between experimental and model responses. Most of them use classical procedures based on gradient methods (see, Lees et al..2007; Pennacchi et al., 2007; Edwards et al., 2000).

However, model-based identification methods produce non-smooth objective functions, which makes the gradient calculation extremely difficult (see, Marwala et al., 1998 and Marwala, 2010). Because of that, computational intelligence techniques, such as Genetic Algorithm, Simulated Annealing and Particle Swarm Optimization are interesting tools for avoiding this kind of problem.

Previously, Castro et al. (2004) studied a non-linear rotor-bearing system, and the unknown parameters were the unbalance magnitude and the viscosity in each bearing. A single objective fitting process, based on Genetic Algorithm, was considered. Weighting factors were chosen for each one of the objective functions, showing how important each objective function is to the adjustment process. Thus, only a single solution was obtained for each set of weighting factors, which may be a local minimum. After that, a refinement of the results was achieved by using a hybrid procedure that combines two meta-heuristic approaches: the Genetic Algorithm and the Simulated Annealing, see Castro et al. 2005 and 2007. A multi-objective Genetic Algorithm for solving this problem was also proposed. In that case, the problem of reaching a single solution for each weighting factor set is overcome, because a Pareto optimum set of solutions is obtained in general, see Castro et al., 2008. More recently, Genetic algorithm parameters were optimized to provide a better convergence in Castro et al. (2012).

Other computational intelligence methods can also be used to find the unbalance parameters through a model-based identification procedure. Simulated Annealing was previously tested by Castro et al. (2005). Another promising method is the Particle Swarm Optimization, which was first proposed by Kennedy and Ebehart (1995). This method is based on social-psychological principles inspired by swarm intelligence.

Therefore, this work proposes a comparison between Genetic Algorithm and Particle Swarm Optimization in the solution of the unbalance identification problem presented in Castro et al., 2012. Thus, the convergence of each method is analyzed based on the iteration needed to reach the global optimum and on the dispersion of the objective function throughout the process.

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2. MATHEMATICAL MODEL

A rotating system can be represented by a combination of substructures, which are the rotor, the journal bearings, and the support structure. In a more general case, the support structure can be considered as rigid. The rotor is supported by oil-film bearings that realize the coupling between the rotor train and the supporting structure. The oil-film bearing forces can be modeled by means of linearized forces, which take into account damping and stiffness coefficients for each rotating speed (see, Lund, 1987). Therefore, the expression of the linearized forces of the oil-film bearing is:

$$\mathbf{F_B} = \mathbf{K_b} \cdot \mathbf{q} + \mathbf{C_b} \cdot \dot{\mathbf{q}} \tag{1}$$

where the bearing stiffness and damping matrices are respectively:

$$\mathbf{K_b} = \begin{bmatrix} \ddots & \vdots & \vdots & \\ \cdots & k_{yy}(\omega) & k_{yz}(\omega) & \cdots \\ \cdots & k_{zy}(\omega) & k_{zz}(\omega) & \cdots \\ & \vdots & \vdots & \ddots \end{bmatrix} \text{ and } \mathbf{C_b} = \begin{bmatrix} \ddots & \vdots & \vdots & \\ \cdots & c_{yy}(\omega) & c_{yz}(\omega) & \cdots \\ \cdots & c_{zy}(\omega) & c_{zz}(\omega) & \cdots \\ & \vdots & \vdots & \ddots \end{bmatrix}. \tag{2}$$

The rotor-bearing system is schematically represented in Fig. 1.

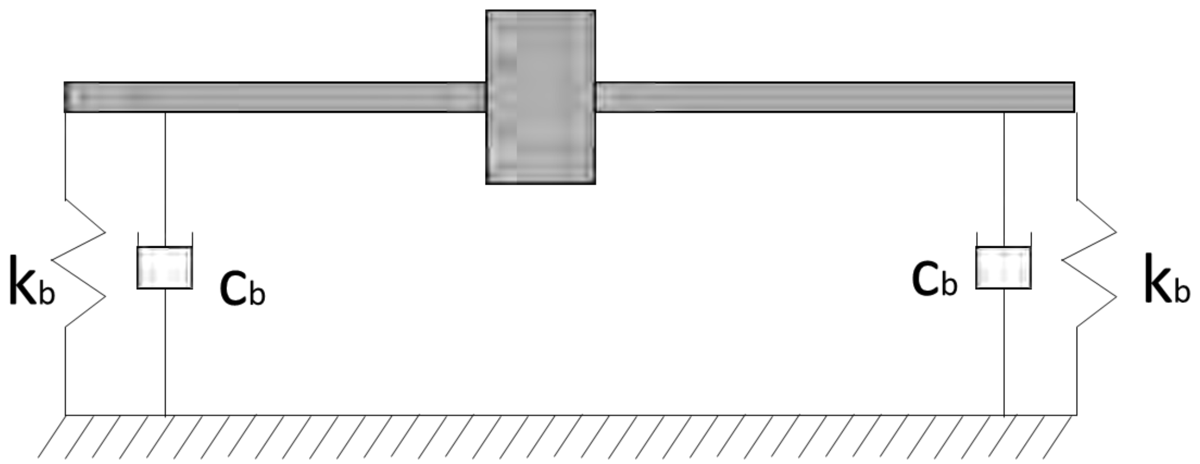

Figure 1. Rotor-bearing system

According to Nelson (1976), the rotor can be modeled by finite element method. Equation (3) presents the equation of motion, which depends on the rotor-bearing system matrices **M** (mass), **C** (damping) and **K** (stiffness), the excitation force **f**(t), and the bending degree of motion $\mathbf{q}(t)^{\mathrm{T}} = \{y_1, z_1, \phi_{y_1}, \phi_{z_1}, \ldots, y_n, z_n, \phi_{y_n}, \phi_{z_n}\}$, where y is the horizontal radial displacement, z is the vertical radial displacement, ϕ_y is the angular displacement related to the y axis, and ϕ_z is the angular displacement related to the z axis. Torsional effects are neglected.

$$\mathbf{M}\ddot{\mathbf{q}}(t) + (\mathbf{C} + \mathbf{C}_b)\dot{\mathbf{q}}(t) + (\mathbf{K} + \mathbf{K}_b)\mathbf{q}(t) = \mathbf{f}(t). \tag{3}$$

The shaft damping matrix **C** contains two parts. The first part is proportional to the stiffness matrix **K** (multiplied by the constant β), and the second part has the gyroscopic effect ($\mathbf{C} = \beta\mathbf{K} + \omega\mathbf{G}$). The bearing stiffness and damping coefficients are included in the corresponding degrees of freedom.

The excitation force is due to the mass unbalance m, with an eccentricity e and phase angle φ, as expressed in Eq. (4), considering a constant rotation speed ω. The axial position of the unbalance is determined by the finite element discretization node. The unbalance force is included in the degrees of freedom related to that node:

$$\mathbf{f}(t) = m \cdot e \cdot \omega^2 \begin{Bmatrix} \vdots \\ \cos(\omega t - \varphi) \\ \sin(\omega t - \varphi) \\ \vdots \end{Bmatrix} \tag{4}$$

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In the frequency domain, the system unbalance response Q can be represented by Eq. (5):

$$Q = \frac{m \cdot e \cdot \omega^2 \cdot \exp(i \cdot \varphi)}{-\omega^2 \mathbf{M} + i \cdot \omega \mathbf{C} + \mathbf{K}} \tag{5}$$

3. SEARCH METHODS

3.1 Genetic Algorithm

The Genetic Algorithm is a search methodology that apply random choice to guide a highly exploitative search, striking a balance between exploration of the feasible domain and exploitation of "good" solutions (Holland, 1971, Goldberg, 1989). This method is analogous to biological evolution. From a biological point of view, it is conjectured that an organism structure and its ability to survive in its environment ("fitness"), are determined by its DNA. An offspring, which is a combination of both parents DNA, inherits traits from both parents and other traits that the parents may not have, due to crossover. These traits may increase an offspring fitness, yielding a higher probability of surviving more frequently and passing the traits on to the next generation. Over time, the average fitness of the population improves.

In GA terms, the DNA of a member of a population is represented as a string where each position in the string may take on a finite set of values. Normally, this "DNA" is represented by a binary string. It makes possible to work with integer and real numbers together in the same optimization process. Therefore, a decoding transforms this variable in binary numbers. However, it is possible to use different kind of codes, such as genes, that are represented by integer and real numbers.

Members of a population are subjected to operators in order to create offspring. Commonly used operators include selection, crossover, and mutation. The selection operator compares the individuals of the population. The individuals that are closest to the optimum point have a major probability to produce a new offspring by crossover and mutation.

The crossover operator combines the data of two different individuals. The mutation operator changes some bits of an individual. The following schema in Fig. 2 represents these two operators.

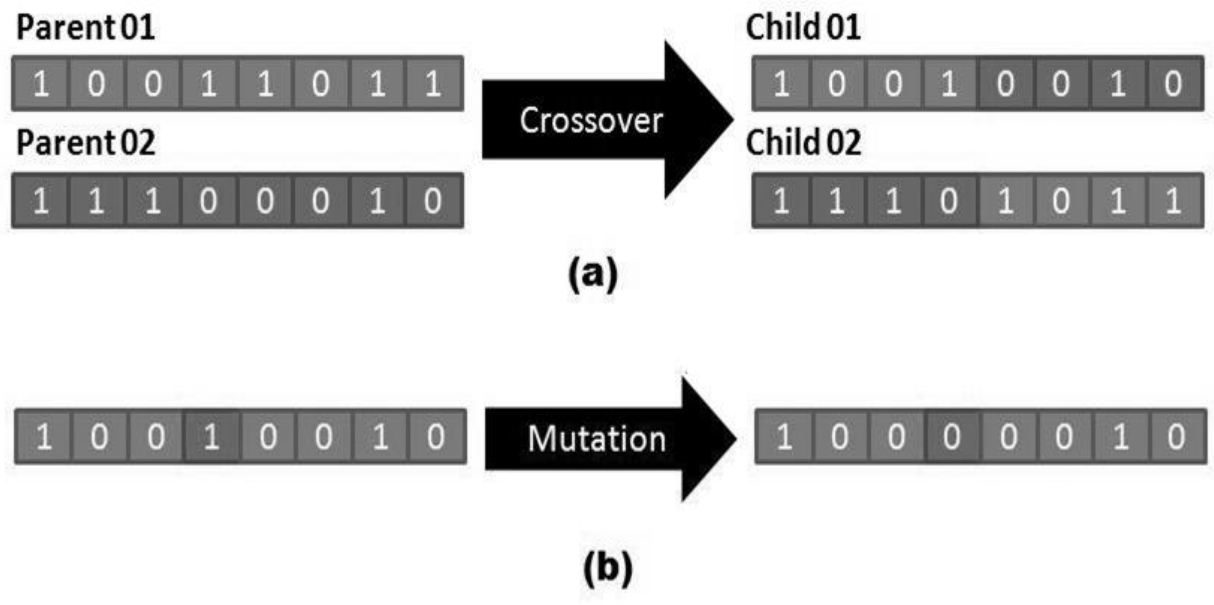

Figure 2. Mutation and Crossover (Camargo et. al, 2010)

GA's are noted for robustness in searching complex spaces and are best suited for combinatorial problems.

There are five GA parameters that influence the process time and the objective function convergence. As the GA is characterized to be a search algorithm, the increase of the operation time brings about better objective function convergence. The GA parameters are:

- Total number of generations: this parameter is characterized to be the stop condition of the genetic algorithm. The increase of the total number of generations results in a linear increase of the computational process time;

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- Population size: it is the number of individuals, who are represented by their chromosomes in each generation. The increase of this parameter increases the probability of objective function convergence. However, the process time increases very significantly;
- Mutation probability: it is the probability of mutation occurrence.
- Mutation rate: it is the rate of bits that can suffer mutation;
- Crossover Probability: it is the probability of the crossover occurrence.

If these parameters are not adjusted to the problem, the convergence cannot occur or it needs a long computational process time to occur.

In order to keep the best results of each generation, the best individuals are kept in the next generation. This process is known as elitist strategy and this rate is also a genetic algorithm parameter.

The GA starts from the generation of a random population. This population is available and its individuals are selected to make the new generation, until the total number of generation is reached. To summarize this process, the steps of GA can be considered:

1. Generate Initial population;
2. Evaluate each individual;
3. Select individual;
4. Make crossover or mutation with selected individual, until the size of population is reached;
5. If the stop criteria is reached (total number of generation), choose the best result and stop. Else, go to step 2.

3.2 Particle Swarm Optimization

The Particle Swarm Optimization (PSO) is an artificial intelligence technique that relies on social behavior pattern or social intelligence, which is observed in several bird species, fish schooling or ants' colonies. It was propose by Kennedy and Ebehart in 1995 with the intention to simulate social behavior. The main idea is based on information systems that are typically constituted by a population of simple agents interacting locally to each other and with their environment. Local interactions between each agents lead to global behavior, although there is not a monitoring center that dictates how the agents should behave. Imagining a birds flocking, if a specific individual, or particle, of this group finds a more promising feed place, the rest of the group change their current course to this new feed place. In optimization process point of view, a bird (group individual) is a possible solution of the problem that flies over the field, which means the search area.

Each optimized particle motion depends on three parameters: sociability factor, individuality (cognitive) factor and inertia weight. The algorithm combines these parameters with a randomly generated number to determine the next location of the particle. Besides, the number of particles and the termination criteria are also parameters of the methodology.

The i^{th} particle position in space is denotes by $\mathbf{X_i} = \{X_{i1}, X_{i2}, \ldots, X_{im}\}$, which is a solution candidate of an optimization problem with m variables. The best previous position (better objective function) of the i^{th} particle is represented by $\mathbf{P_i} = \{P_{i1}, P_{i2}, \ldots, P_{im}\}$. The best global position, considering all particles, is $\mathbf{P_g} = \{P_{g1}, P_{g2}, \ldots, P_{gm}\}$. The new particle position variation is given by $\mathbf{V_i} = \{V_{i1}, V_{i2}, \ldots, V_{im}\}$ and is calculated by:

$$\mathbf{V_i} = W \cdot \mathbf{V_{i_{previous}}} + c_1 \cdot rand_1 \cdot \left(\mathbf{P_i} - \mathbf{X_{i_{previous}}}\right) + c_2 \cdot rand_2 \cdot \left(\mathbf{P_g} - \mathbf{X_{i_{previous}}}\right) \quad (6)$$

Where W is the inertia weight, $rand_1$ and $rand_2$ are ramdom number between 0 and 1, c_1 is the individuality or cognitive factor and c_2 is the sociability factor. The new particle position is:

$$\mathbf{X_i} = \mathbf{X_{i_{previous}}} + \mathbf{V_i} \quad (7)$$

The termination criteria can be determined by the result convergence or even a maximum number of iterations.

If the individuality or cognitive factor is set to zero, only the social behavior determine the search process. On the other hand, when the sociability factor is neglected only individual knowledge is important to define the particle way to best solution (feed place).

The PSO steps are:

1. Create initial particle swarm;
2. Start iterations;
3. Evaluate objective function to rank the position;
4. Calculate position variation and new position using Eq. (6) and (7) respectively.
5. If termination criteria is reached (total iteration), choose the best result and stop.

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4. EXPERIMENTAL SETUP

To develop and test the balancing strategy, the test-rig shown in Fig. 3 was used to acquire an experimental unbalance response of the rotor bearing system. This experimental test-rig has two hydrodynamic bearings with a radial clearance of 90 µm and one concentrated mass placed in the shaft middle. The bearing radius is 31 mm and its length is 20 mm and an AWS 32 oil lubricates the bearings. The distance between the bearings is 600 mm and the shaft diameter is 12 mm. The concentrated mass consists of a disk of external diameter of 95 mm, a length of 47 mm, and a mass of 2.3 kg. A journal with a diameter of 40 mm and length of 80 mm is set on the shaft in a position closer to the bearing opposite to
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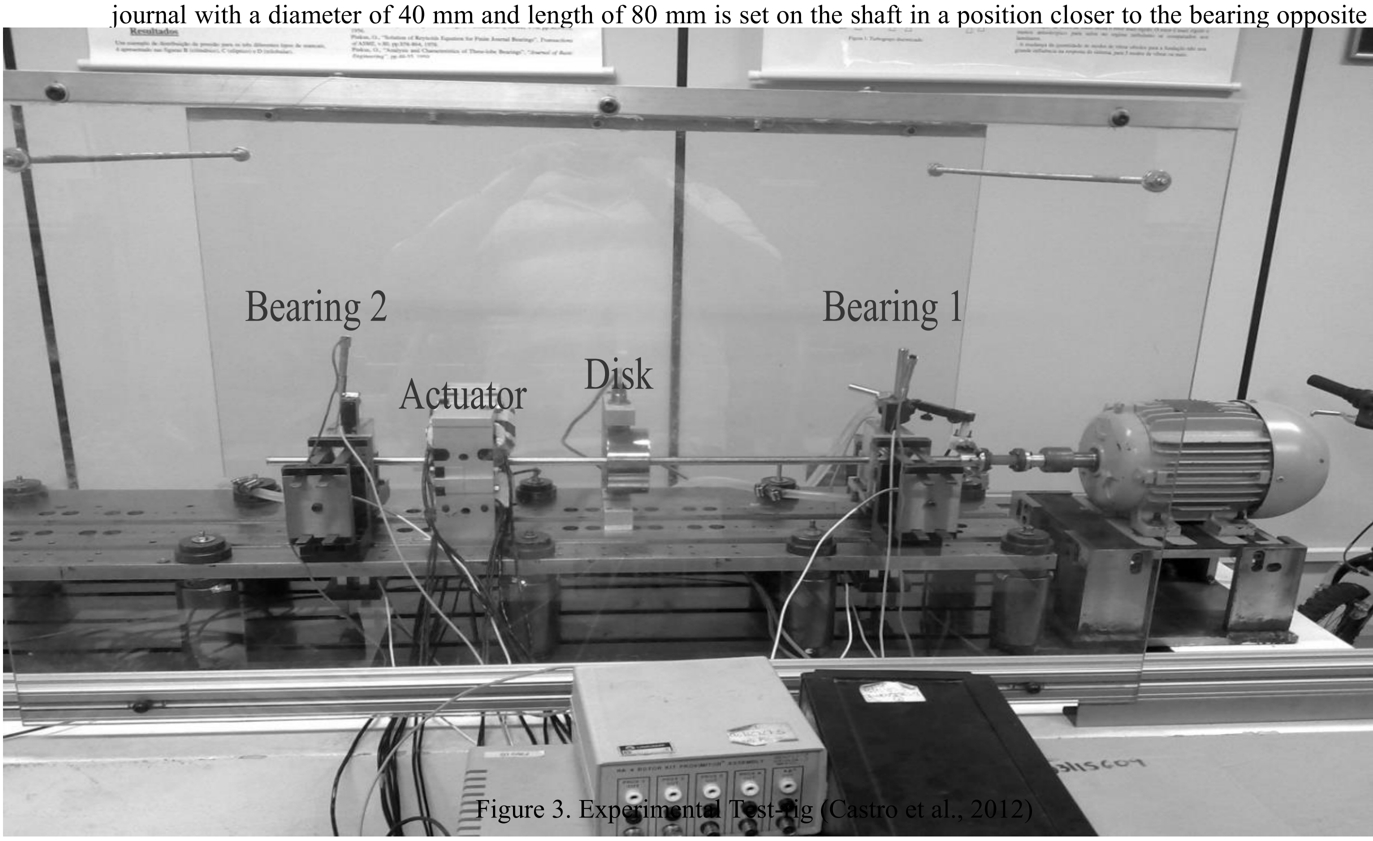

Figure 3. Experimental Test-rig (Castro et al., 2012)

5. METHODOLOGY APPLICATION AND RESULTS

A model updating procedure was first applied to determine the bearing stiffness and damping coefficients. This process was presented by Castro et a. (2012). To summarize these results, Fig. 4 shows these coefficients for each rotation speed. Therefore, the complete rotor-bearing model presents a good accuracy to the experimental model. This is extremely important to perform a model-based identification process, as it is proposed in this work.

The unbalance response (amplitude and phase) on bearing 1 is presented in Fig. 5, in order to exemplify how the model approaches the experimental results. The blue and red lines means horizontal y and vertical z flexural direction. The points are the experimental results. Because of possible damage to the test-rig, the unbalance response was not accomplished with rotation speed around the critical speed (22.5 Hz).

A known unbalance was introduced to the central disc of the test-rig. In that way, it is possible to induce a vibration with a known excitation. The GA and PSO are applied to identify this unbalance, which is described by its magnitude ($m{\cdot}e$ from Eqs. (4) and (5), phase φ and axial position, represented by a node of the finite element discretization). The objective function of both search (optimization) procedures is based on the difference of the experimental and model responses aand it is given by:

$$f = \sum_{i=1}^{ns} w_i \left(\sqrt{\left(Re(qe_i) - Re(qs_i)\right)^2} + \sqrt{\left(Im(qe_i) - Im(qs_i)\right)^2} \right) \tag{8}$$

where qe and qs are the experimental and simulated displacements respectively, ns is the number of sensors and w is a weighting factor to each measured degree of freedom. The weighting factor can be used to evidence a higher confidence for a specific measured degree of freedom. Moreover, weighting factor could also be used to fit the difference of magnitude.

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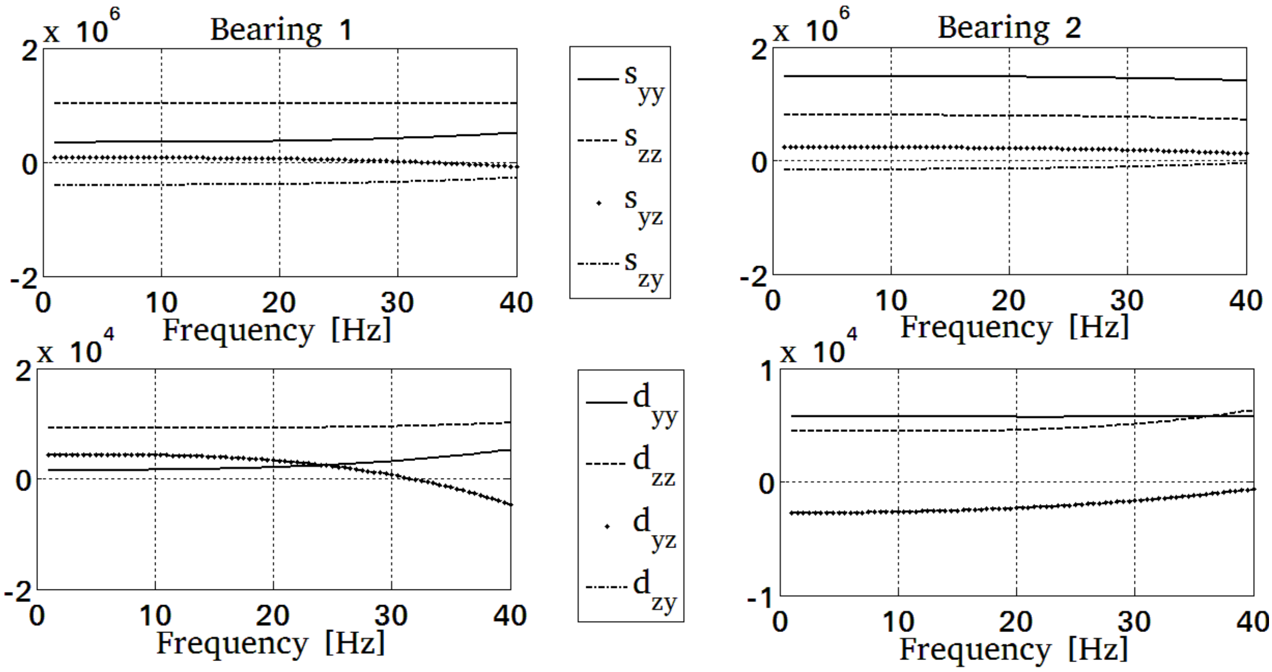

Figure 4. Bearing coefficients (Castro et al., 2012)

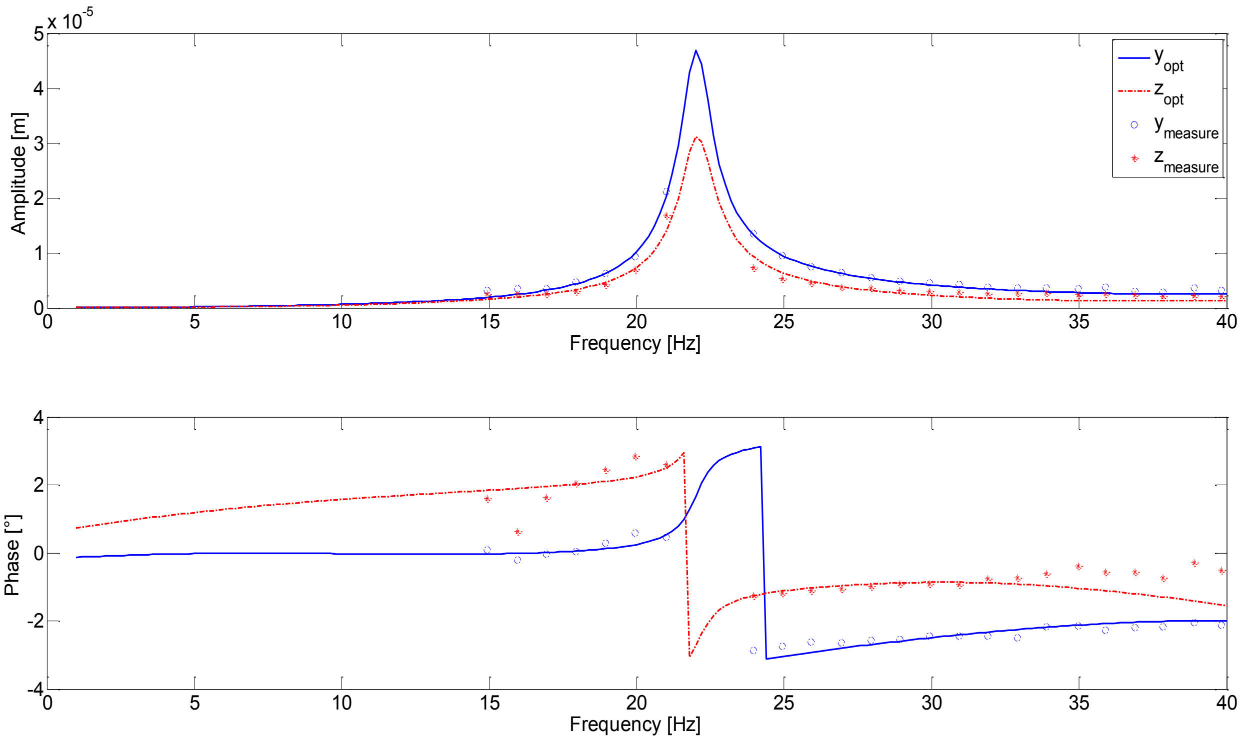

Figure 5. Bearing 1 Unbalance Response (Castro et al., 2012)

The GA parameter where obtained by Castro et al. (2012), when it was optimized for this problem through factorial planning. These parameters are shown on Table 1. In order to compare the convergence of GA and PSO, the total iteration and the number of particles have the values of generations and population size respectively, because they have the same meaning for their own algorithm. The product of both parameters (generations and population size, or iterations and

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number of particles) represents the number of evaluation of the objective functions. The first is the number of iterations and the second is the size of possible solutions used to sweep the optimization area. The others PSO parameters are also present on Table 1. They were selected to improve the method convergence. It is important to highlight that the number of generations or iterations is more than enough for the problem convergence. It is assumed higher values to guarantee the convergence, because both methods depend on random factors.

Table 1. Search methods parameter.

Genetic Algorithm	Particle Swarm Optimization
Generations = 100	Iterations = 100
Population Size = 100	Number of Particles = 100
Crossover Probability = 70%	Inertia Weight = 0.3
Mutation Probability = 10 %	individuality or cognitive factor = 1
	sociability factor = 1

Table 2 shows the best adjusted values (for GA and PS) and the expected values of unbalance parameter that were inserted in the test-rig. The best objective function is also shown on this table.

Table 2. Unbalance parameters.

Unbalance parameters	Expected value	Best GA result	Best PSO result
Unbalance moment [kg·m]	$1.425 \cdot 10^{-4}$	$1.419 \cdot 10^{-4}$	$1.419 \cdot 10^{-4}$
Unbalance phase [°]	0	5.3362	5.3368
Unbalance position [node]	8	8	8
Objective function	-	0.06788	0.06788

Both methods were able to reach the expected results. There is a shift on phase estimation (5°), but it is acceptable, because this phase discrepancy is lower than the difference between the holes used to fasten the unbalance to the experimental test-rig, which are positioned at an angle of 15° from each other. However, there are some differences on the method convergence as it is highlighted in Fig 6. Figure 6(a) presents the best objective function (minimum) for each iteration (or generations) for the PSO (blue solid line) and GA (blue dash-dot line). Besides, Figure 6(b) shows the detail of the first iterations (or generations). The PSO reaches the global minimum faster. For the tested case, the minimum objective function is obtained at the 10th iterations. In the case of the GA, the best objective function is reached at the 24th generation. Besides, the objective function standard deviation of PSO process approach to zero in the 11th iteration. This means that from the 11th iteration all particles reaches the first result. In the case of the GA, the objective function standard deviation never reaches zero. This is an important characteristic of the GA, because this characteristic allows the method to avoid convergence in any local optimum point, providing a mechanism to escape from this point and seek a global optimum point.

The variance on GA convergence is higher than in PSO. The GA objective function mean is always higher than the minimum objective function value and there is considerable variations on its standard deviation. This is an important characteristic of GA, because this diversity allows the GA to search better results. The main parameter for this behavior is the mutation probability. If there is not mutation on GA process, the convergence tends to reach a local minimum with low or null diversity. On the other hand, the diversity of the PSO is low in the first interactions and null after the global minimum is located. Because of the process characteristic, the particle sweep all the search area and seek for the global optimum. Figure 7 (a) – (d) shows the particle positions over the iterations 1, 3, 10 and 20 respectively. On the first one, the position diversity is high, but a point close to the global minimum is found (highlighted in red). On the third iteration, it is clear that all particle is moving to the region were the global minimum is located. The diversity is low on the tenth iteration and all particle reached the global minimum at the twentieth iteration. This convergence process confirm the Fig. 6 observation about the PSO process. The convergence is fast and there is a low (or null) objective function standard deviation after this convergence.

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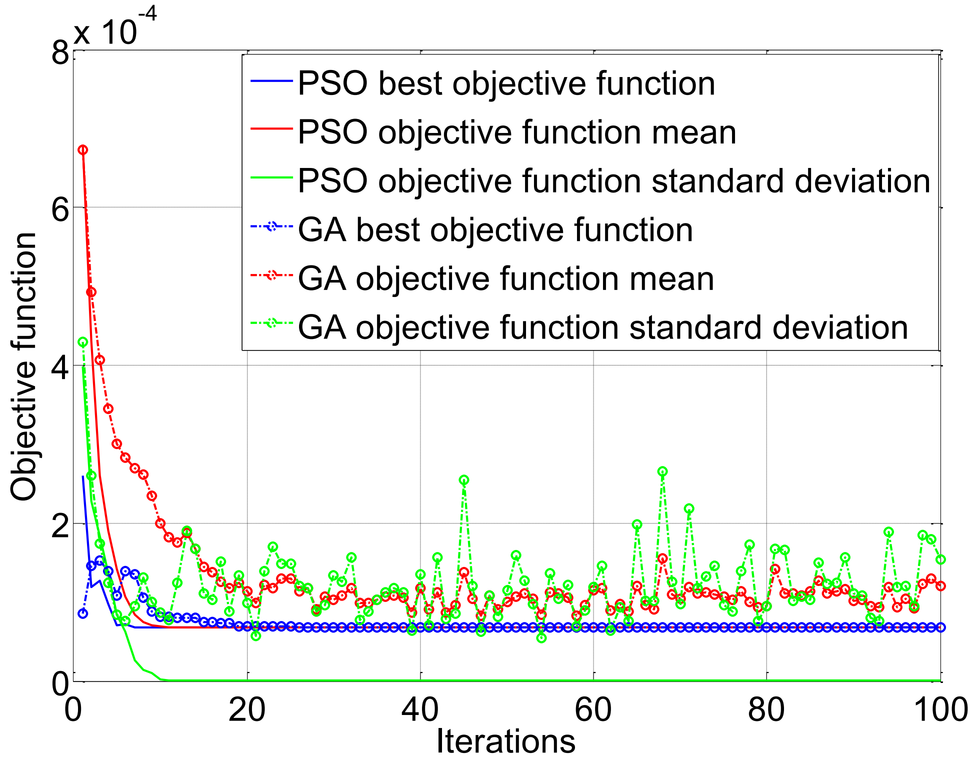
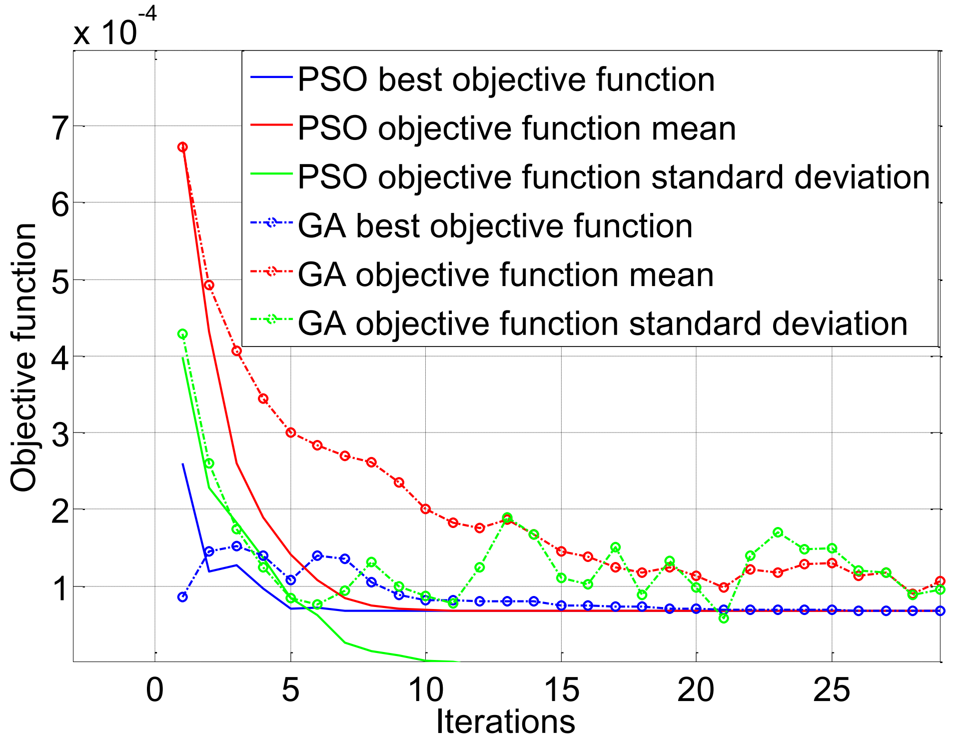


(a)



(b)

Figure 6. Identification convergence: (a) all iterations/generations; (b) firsts iterations/generations.

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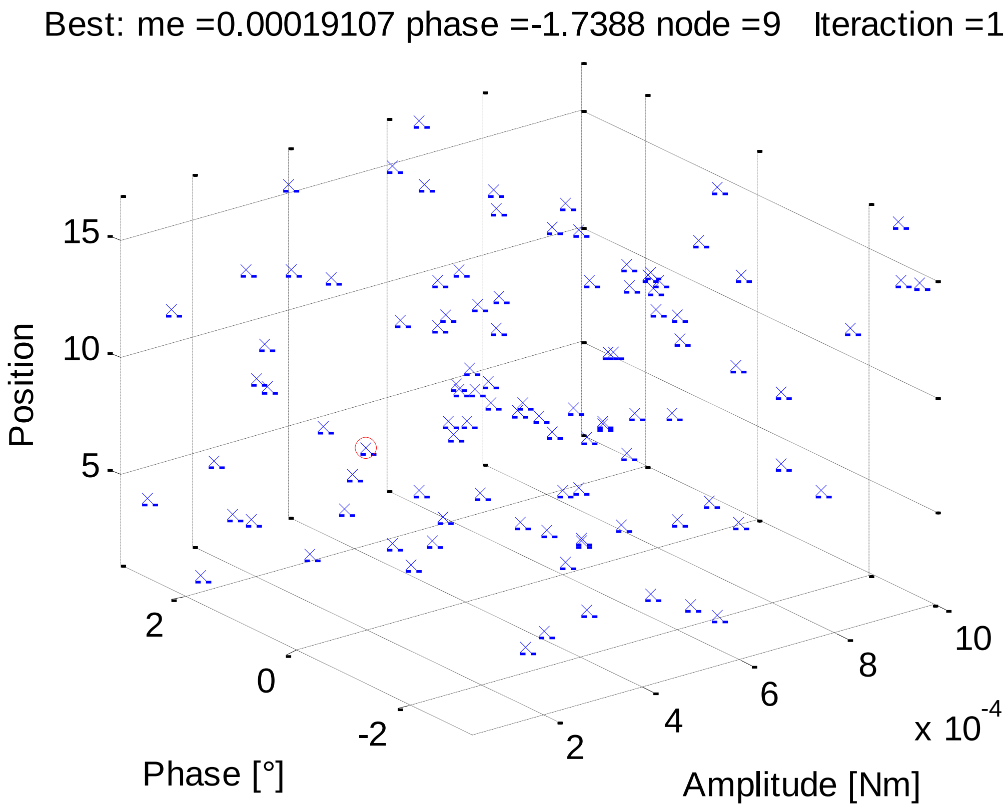
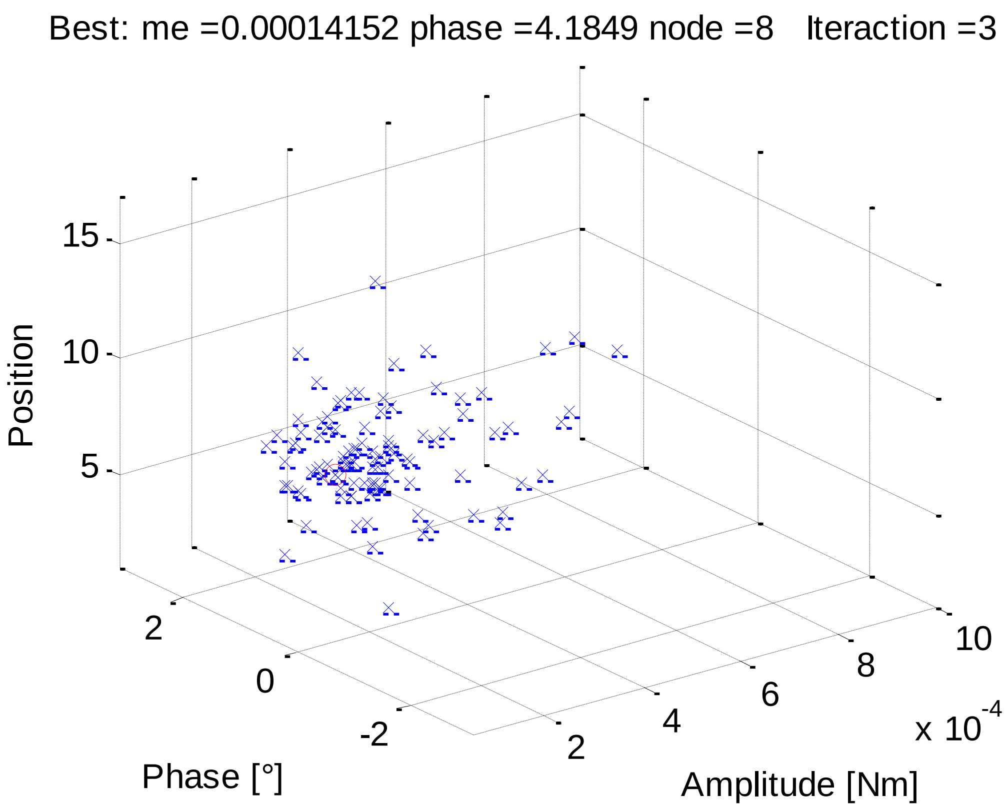


(a)



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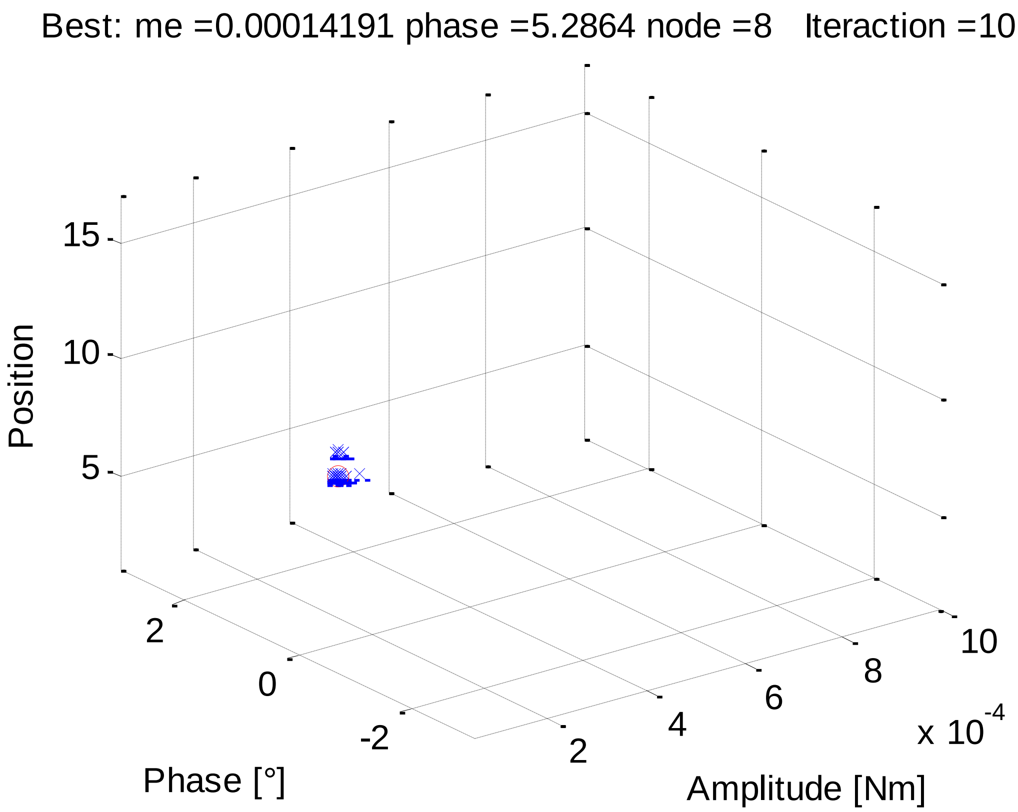

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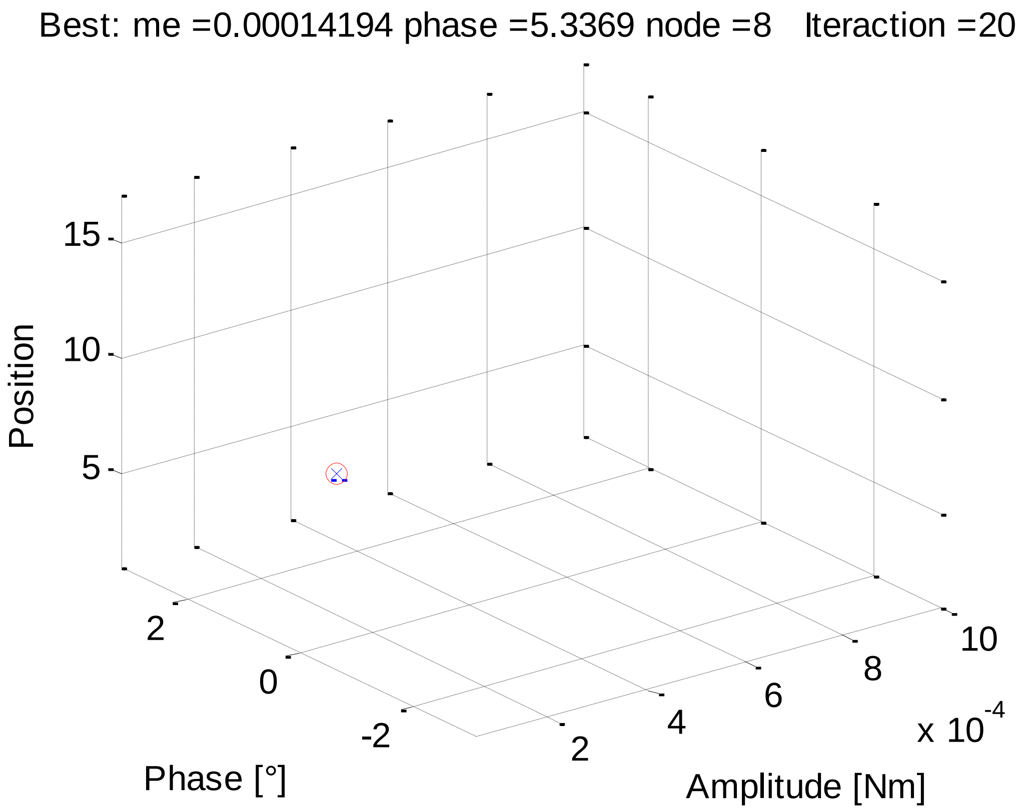

(d)

Figure 7. Particle Swarm set in several iterations: (a) iteration 1; (b) iteration 3; (c) iteration (10); iteration (20).

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6. CONCLUSIONS

This paper deals with a comparison between GA and PSO applied to unbalance parameter identification.

A rotor-bearing updated model was used, in order to ensure the accuracy between the test-rig experimental results. This fact highlighted the importance of representative model, because if the model does not fit the physical system, uncertainties are included in the parameters identified.

To indicate the difference between the experimental and model responses, an objective function is accomplish, considering the experimental displacement in each sensor and

Both method were able to find the expected parameters, excepted for a discrepancy in phase estimation, which is explained by the angle between the holes used to fasten the mass unbalance to the test-rig, which is equal to 15° that is higher from the difference between expected and reached values that is 5°.

The PSO converges faster than genetic algorithm. On 10^{th} iteration the PSO reaches the global minimum, while the GA got this value on the 24^{th} generation. This PSO characteristic is an important aspect of the method, because a faster method is desirable if the application demands swift response.

However, the variance on the objective function on the PSO tends to zero after the algorithm reaches the global minimum. In the case of the GA, the variance is always higher, which is an important characteristic of the method, because it helps the process to avoid local minimum. Although the PSO is faster than GA, the GA diversity can be an important advantage.

This comparison should be extend to multiple fault identification process in a future work, in order to determine which method fits better taking into account a more complex problem, considering that both search methods presented different advantages.

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