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COMPARISON IN THE APPLICATION OF MULTI-OBJECTIVE FIREFLY ALGORITHM, GENETIC ALGORITHM AND PARTICLE SWARM OPTIMIZATION IN UNBALANCE IDENTIFICATION IN ROTATING MACHINERY.

Andrei Bavaresco Rezende
Cassio Pereira de Paula
Helio Fiori de Castro
University of Campinas – School of Mechanical Engineering - 13083-860 Campinas SP – Brasil
abavaresco@fem.unicamp.br
cassio2014@fem.unicamp.br
heliofc@fem.unicamp.br

Abstract. *Rotating machines operate important functions in the industries today. Therefore, the study of rotordynamic models occupies a prominent position in the rotating machinery context due to the significant amount of phenomena that can occur during operation of such equipment. The main fault that occurs in rotating systems is unbalance. So it is interesting to identify the failure parameters from the minimization of the differences between the model and the experimental responses. A multi-objective problem is characterized, because the difference between model and experimental response in each monitoring degree of freedom is an objective function to be minimized. Therefore, meta-heuristics search methods are interesting tools to solving this problem. This work propose a comparison of the performance between the Multi-objective methods based on Genetic Algorithm, Firefly Algorithm and Particle Swarm Optimization. In the first method, the optimization methodology is based on evolutionary genetic algorithm and is intended to evolve a set uniformly distributed solutions belonging to the Pareto optimal set. The second method, the algorithm is based on the bioluminescent behavior of fireflies colonies. And last method is the multi-objective Particle Swarm Optimization, which is a population based stochastic optimization technique inspired by the social behavior of bird flocking or fish schooling.. In that way, this work proposes a comparison between the optimization methods above described through an application in unbalance identification problem in rotating system.*

Keywords: *Multi-objective Firefly Algorithm, Multi-objective Genetic Algorithm, Multi-objective Particle Swarm Optimization, rotating system, unbalance identification.*

1. INTRODUCTION

Nowadays rotating machines are present in several important functions in the industries. It is very important to detect possible problems before them occurs. Therefore, the study of rotordynamic models is considered a prominent position in the rotating machinery context, due to the significant amount of phenomena that can occur during operation of such equipment. The main faults that occur in rotating systems is unbalance. Thus, in order to identify the failure parameters, it is necessary to minimize the difference between the model and the experimental responses. Several models were developed to identify these parameters. Many of them are based on gradient methods (see, Lees et al..2007; Pennacchi et al., 2007; Edwards et al., 2000). Though, these methods have in the gradient calculation a difficult process, because of the presence of a non-smooth objective functions (see, Marwala et al., 1998 and Marwala, 2010). Thus, meta-heuristics multi-objective search methods, such as Genetic Algorithm, Firefly Algorithm and Particle Swarm Optimization are interesting computational tools to avoid this problem.

Anteriorly, a non-linear rotor bearing system was studied by Castro et al. 2004, considering that the unbalance magnitude and the viscosity in each bearing were the unknown parameters. It was used a single objective fitting process, based on Genetic Algorithm, where it was assigned weighting factors for each one of the objective functions, showing the significance in the fitting process of each objective function. After that, to refine the results was used a hybrid procedure that combines two meta-heuristics approaches: Genetic Algorithm and Simulated Annealing, see Castro et al. 2005 and 2007. In these previous cases, it was not proposed solving this problem using a multi-objective Genetic Algorithm. On the other hand, instead of one single weighted solution, a Pareto optimum set as solution was proposed by Camargo et al., 2010. More recently, Genetic Algorithm and Particle Swarm Optimization (PSO) were compared in the solution of this problem. The convergence of each method is analyzed based on the number of iteration needed to reach the global optimum and on the dispersion of the objective function throughout the process. The PSO is a population based stochastic optimization technique inspired by the social behavior of bird flocking or fish schooling, see Castro el al. 2013.

A firefly algorithm is a computational intelligence method also used, in this work, to find the unbalance parameters. The method is based on the bioluminescent behavior of fireflies colonies and each firefly has a certain attraction for the intensity brightness issued for him, and this intensity is related to the objective function. The algorithm is organized considering that a firefly is a possible solution of the problem and moves randomly in the sample space, attracting or being attracted to other fireflies.

Therefore, this work proposes a comparison between Multi-objective Genetic Algorithm, Firefly Algorithm and Particle Swarm Optimization through an application in unbalance identification problem in rotating system presented in Castro et al., 2013. The convergence of each method is analyzed based on the iteration needed to reach the global optimum.

2. MATEMATICAL MODEL

One way to represent the rotating system is dividing the main system in substructures. These are the rotor, the journal bearings and the support structure. The foundation is assumed rigid in this paper. The oil-film bearings have important function in the rotor system, because it supports the rotor and perform the coupling between the rotor train and supporting structures. To simplify the mathematical calculation is utilized the process of linearized of the forces, which consider damping and stiffness coefficients for each rotating speed (see, Lund, 1987). Therefore, the equation of the linearized forces mentioned is:

$$[F_{\mathrm{B}}]=[K_{\mathrm{b}}]\{q\}+[C_{\mathrm{b}}]\{\dot{q}\} \tag{1}$$

Where the bearing stiffness and damping matrices are respectively:

$$K_{\mathrm{b}}=\begin{bmatrix} \ddots & \vdots & \vdots & \\ \cdots & k_{\mathrm{yy}}(\omega) & k_{\mathrm{yz}}(\omega) & \cdots \\ \cdots & k_{\mathrm{zy}}(\omega) & k_{\mathrm{zz}}(\omega) & \cdots \\ & \vdots & \vdots & \ddots \end{bmatrix} \text{ and } C_{b}=\begin{bmatrix} \ddots & \vdots & \vdots & \\ \cdots & c_{\mathrm{yy}}(\omega) & c_{\mathrm{yz}}(\omega) & \cdots \\ \cdots & c_{\mathrm{zy}}(\omega) & c_{\mathrm{zz}}(\omega) & \cdots \\ & \vdots & \vdots & \ddots \end{bmatrix} \tag{2}$$

The rotor-bearing finite element is schematically represented in Fig. 1.

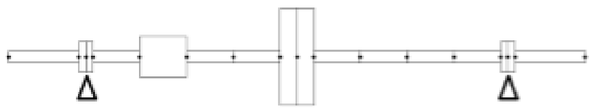

Figure 1 – Rotor Finite element model, (Castro et al., 2012)

The finite element method can be used to model the rotor system (Nelson, 1976). Equation (3) is the equation of motion at the system and it is compose by matrices [M], [C], [K], that are matrices at mass, damping and stiffness of the rotor. In the equation of motion, it is also considered the excitation force $\{f(t)\}$ and the degree of the system $\{q(\mathrm{t})^{\mathrm{T}}\}=\{y_1, z_1, \phi_{y1}, \phi_{z1}, \ldots, y_n, z_n, \phi_{yn}, \phi_{zn}\}$, 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.

$$[M]\}\{\ddot{q}(t)\} + ([C] + [C_{\mathrm{b}}])\{\dot{q}(\mathrm{t})\} + ([K] + [K_{\mathrm{b}}])\{q(t)\} = \{f(t)\} \tag{3}$$

It is important to emphasize that the damping matrix [C] contains a part that is proportional to the stiffness matrix [K], and another part that correspond to the gyroscopic effect ([C] = β [K] + ω [G]). The excitation force is given by the Eq. (4), where m is the unbalanced mass, e is the eccentricity, φ the phase angle and ω the rotation speed that is constant. The finite element discretization is used to define at the axial position (node) where the unbalance is located.

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

The system unbalance response is given by Eq. (5).

$$Q = \frac{me\Omega^2 e^{i\varphi}}{\left(K\text{-}M\Omega^2\right)+i\Omega C} \tag{5}$$

3. OPTIMIZATION METHODS

3.1 Multi-objective Genetic Algorithm (NSGA II)

The Genetic algorithm developed by Holland in 1975 was inspired on evolution and genetic mechanism. Created as problem solution method, which used models based on nature concepts where the evolution is key-element to the project and method implementation (Camargo, 2010). This method normally is used to problems that are difficult to solve with conventional methods. It has been used as search method and optimization in many areas. The reason of success is due the global search, the facility to use and extensive applicability. Furthermore, it is not necessary to know the domain of problem which reduces the computational cost (Vafaie and De Jong, 1992).

In genetic algorithm method, in a generation each individual is evaluated through its fitness (objective function). Along the generations, the population moves to the best solution space of problem domain. In the method process, it is used a serial of stochastic operators to manipulate the genetic code. In the most of Genetic Algorithm, there are operators to select the individuals that and will form, through reproduction, new individual group to be part of the future population. The most usual reproduction operators are crossover and mutation.

Although the genetic algorithm has an easy form to be implemented, there are some parameters that are important to adjust to have a good objective function convergence. These parameters are the number of generations, population size, mutation probability, crossover probability. Number of generations is how much iteration the algorithm will execute and is considered as stop condition. Population size is the number of individuals that participle in each iteration. Mutation probability is the chance of the mutation occurs on genetic combination. Crossover probability is the chance of the individual be selected for crossover.

The multi-objective solutions are based on the method that obtains a set of solution and not one single best solution. On multi-objective algorithm, the performance value is calculated to each individual using the objective functions. Thus, the generation process of new population is interactivity repeated until the genetic algorithm find the set of viable solution or satisfy the stop condition. Then, a set of non-dominated solution (Pareto front) is obtained. A Pareto front (or non-dominated solutions) is a set of possible solutions that it is not possible to improve any objective function by a change in a solution, without a depreciation of any other objective function.

Along the years, it was developed several variations of Multi-objective Genetic Algorithm. In this work, it is used the Non-Domination Sorted Genetic Algorithm II (NSGA II) that is a modified version of NSGA. The NSGA is a multi-objective genetic algorithm that results in a selection of the non-dominated solution and maintains the diversity of this solution. In each iteration, the population is divided in groups that are distributed in non-dominated front. This process is used to select the individuals that will participate in the reproduction process.

In the NSGA II, it was included the elitism and a measure of the distance between an individual and its own neighbors, which is called crowding. The elitism is a mechanism where the individuals that participate in reproduction process are passed to the next generation. As higher the distance between the individuals of Pareto set, better the population diversity is, (Soares, 2008). In the first front, there are the non-dominated individuals, and in the second front, there are the individuals dominated by the first front. To first front it is attributed a number 1, and to the second front the number 2. Successively fronts are created based on this classification. Then, a rank is created for each these individual. Therefore, to use the fitness value of each individual, it is considered a crowding distance parameter and the rank classification. As better is the classification and higher is the diversity of the population, the selection has a higher probability to happen. The binary tournament selection is used to select the individuals that will pass by the reproduction process. The process is repeated, always considering the rank and the crowding distance.

To summarized, The NSGA II steps begin with the generation of population randomly. Population is sorted based on non-domination and the crowded distance is calculated. The non-dominated individuals are selected to do the crossover and mutation. This process is repeated until the condition stop to be satisfied. The principal steps summarized are:

1. Generate Initial Population
2. Sorted the Population using non-dominated method
3. Calculate the Crowded distance
4. Make crossover or mutation with the selected individual (non-dominated)
5. If the stop criterion is achieved, selected the best result and finish.
6. Else, go to the step 2.

3.2 Multi-objective Firefly Algorithm (MOFA)

Firefly Algorithm was recently developed nature-inspired metaheuristic by Yang in 2009, and it was based on behavior social of fireflies. This method considered three ideal hypotheses: The fireflies are unisex and anyone can attract or be attracted by other fireflies; Attraction of a firefly is proportional to luminosity issued by him and decrease with the increase of distance. Then one firefly less bright will move towards to the brighter. If there is not one brighter to a respective firefly, it will move randomly; the brightness of a firefly is related to the objective function, (Yang, 2009).

For a maximization problem, the brightness can simply be proportional to the value of the objective function. As both light intensity and attractiveness affect the movement of fireflies in the firefly algorithm, it is necessary to define their variations. In the simplest case of maximum optimization problems, the brightness I of a firefly at a particular location x can be chosen as $I(x) \propto f(x)$, (Yang, 2013).

Attractiveness: The attractiveness β is determines how much one firefly is attractive by other and it is determined by the light intensity. The attraction between two fireflies is inversely proportional to the distance between them. Can be calculated using the equation below:

$$\beta=\beta_o e^{-\gamma r^2} \tag{6}$$

where r is the distance between firefly i and firefly j, γ is the light absorption coefficient and β_o is the maximum attractiveness so when $r = 0$. An important point is that the value of r is the Cartesian distance between two fireflies i and j, $r_{ij}=\|x_i - x_j\|$.

Movement: Each firefly move iteratively according to the follow rules: The attractiveness of other firefly with greater emitted light varies according to the distance and a random pitch vector to avoid premature convergence. Thus when one firefly i is less attractive then a firefly j the movement at x_i toward to other firefly x_j is described by:

$$x_i^{t+1}=x_i^t+\beta_o e^{-\gamma r^2{}_{ij}}\left(x_j^t-x_i^t\right)+\alpha_t\epsilon_i^t \tag{7}$$

where α_t is the randomization parameter and ϵ_i^t is a vector of random numbers draw from a uniform distribution. The second term characterizes the attraction suffer by the firefly i. The location of firefly is updated sequentially in each iteration cycle thought at comparison and updating each pair of firefly. It is worth to point out that the value of light absorption coefficient γ has a great importance, because it determines the speed of the convergence and how the Firefly behaves. This value, in general case, varies from 10^{-5} to10^5, (Yang, 2013).

To introduce the multi-objective optimization to a firefly algorithm it is used the theory of Non-dominated sort. So, it is taken into account a set of solution (Pareto Front) represented by the fireflies, and it is compose by all best solutions that are, consequently, the brightest individuals. In the search space, there are many brighter fireflies, and in each comparison, the less bright around them will move toward them.

The parameters to be adjusted on the algorithm are the attractiveness β_o, light absorption coefficient γ, the size of population, number of iteration and the up and down searched parameters limits. The algorithm starts with the initialize of the population of n fireflies spread uniformly. A fireflies pairs is compared with respect to their brightness and the least bright moves to the brighter firefly. This process is repeated until the criterion stop is reached. The principal steps summarized are:

1. Generate the initial population.
2. Evaluate the fireflies.
3. Move the less bright firefly toward bright one.
4. If the stop criterion is satisfied selected the best results (non-dominated ones). Else back to the step 2

3.3 Multi-objective Particle Swarm Optimization (MOPSO)

Proposed by Kennedy and Ebehart in 1995, the Particle Swarm Optimization (PSO) is a heuristic search technique that simulates the social behavior of a birds flock or fishing schooling, aiming to find food. Similar to evolutionary algorithms, PSO exploits a population, called a swarm, of a potential solution, called particles, which are modified stochastically at each iteration of the algorithm. However, the manipulation of swarm differs significantly from that of evolutionary algorithms (Parsopoulos & Vrahatis, 2008).

In the behavior of birds flocks, it is possible realize that the group follow a leader bird, which is who has found the more promising place food. At the moment that another bird to find a better place food, the group will follow this one. The same thinking is used to PSO, where the particles move toward to the best particle (leader).

Besides population size and the number of iterations, the PSO algorithm depends on the selection other tree parameters known as sociability factor, individuality factor and inertia weight. These parameters are combined with a randomly generated number to determine the position of the particle.

The update of the particles position depends on the previous position vector x_i and the velocity vector v_i. This velocity vector can be calculated by:

$$V_{\mathrm{i}}=WV_{\mathrm{i}_{\mathrm{previous}}}+c_1 rand_1\left(P_{\mathrm{i}}\text{-}X_{\mathrm{i}_{\mathrm{previous}}}\right)+c_2 rand_2\left(P_{\mathrm{g}}\text{-}X_{\mathrm{i}_{\mathrm{previous}}}\right) \tag{8}$$

where W is the inertia weight that reduces in each iteration, $rand_1$ e $rand_2$ are the random number that vary between 0 and 1, X_i is a solution candidate of the problem, P_i is the best previous position to the i^{th} particle, P_g is the best global position (knowledge of the leader). The parameter c_1 is individuality or cognitive factor, and c_2 is the sociability factor. These two parameter control the influence of the personal and global best particles. The new position depends on previous position and the velocity calculated. It is described by:

$$X_{\mathrm{i}}=X_{\mathrm{i}_{\mathrm{previous}}}+V_{\mathrm{i}} \tag{9}$$

The process starts initializing the population of swarm, which includes both the position of the particles. One external archive is initialized to store the leaders and they are the non-dominated solutions in the swarm. Then, the particles are evaluated and the particle position is updated in each iteration. After the stop criteria is reached, the archive is returned as the result of the search and these results form the Pareto front, where there are only the non-dominated solutions. The principal steps are presented by:

1- Initialize Swarm and Leader Archive
2- Selected the leader and updated the position of each particle
3- Selected the best particle.
4- Updated the leader archive.
5- If the condition stop is reached return the archive with the result. Else return to step 2.

4. EXPERIMENTAL SETUP

In order to get the real response of unbalance rotor bearing system, it was used a test-rig that is illustrated on Fig. 2. This system is composed by one concentrate mass that is a disk with a mass of 2,3 kg, an external diameter of 95 mm end a length of 47 mm. Other parts of the system are two hydrodynamic journal bearings. The radial clearance of the bearings is 90 µm and the shaft has diameter at 12 mm. Furthermore, the bearing radius and bearing length are 31 mm, 20 mm respectively. The distance between both bearing centers is 600 mm. An AWS 32 oil lubricates the bearings. In addition, there is also a journal fixed in the shaft close to bearing 2. This journal has diameter of 40 mm and length of 80 mm and it is necessary due to an electromagnetic actuator, which is not applied in this work, but belongs to the test-rig. Sensors are installed immerged in the oil film of bearings to obtain the displacement of the shaft. In addition, another two displacement sensors are used to monitor the orbit of the rotor mass.

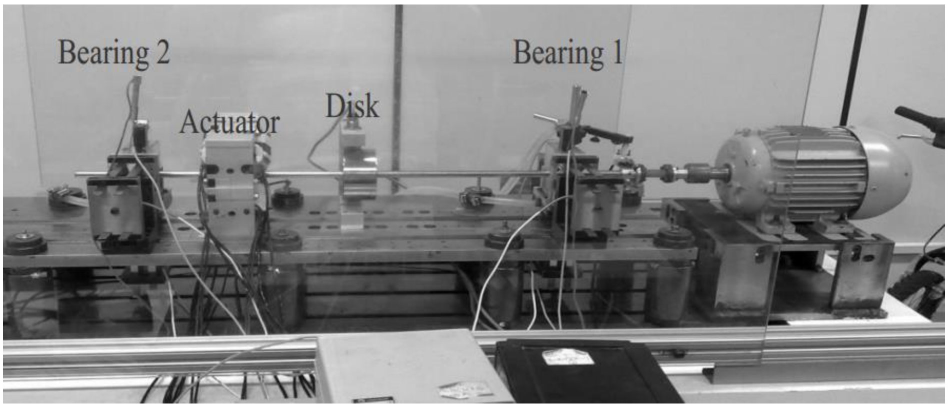

Figure 2 – Experimental test-rig, (Castro et al., 2013)

5. METHODOLOGY APPLICATION AND RESULTS

The first step is to obtain the stiffness and damping coefficients by the application of an updating model procedure, as presented by Castro et. al., 2012. Therefore, all parameters of the Eq. (2) can be known and consequently the completed rotor-bearing model in Eq. (3) can be considered.

Then, an unbalance mass is fixed in the center disc of test-rig and the experimental response of the system were obtained. As the unbalance mass parameters are known, it is possible to set a comparison standard for the identification procedures. Thus, the identification methods NSGA II from MATLAB toolbox, MOFA end MOPSO (the last 2 developed for this work) are applied to obtain the failure parameters that are the unbalance amplitude ($m{\cdot}e$), phase angle (φ) and axial position (represented by the node of the finite element discretization Fig. 1). The objectives functions considered take into account the difference between numerical and experimental response of bearing degrees of freedom.

$$f_i = \sqrt{(Re(qe_i) - Re(qs_i))^2} \tag{10}$$

$$f_{i+ns} = \sqrt{(Im(qe_{i+ns}) - Im(qs_{i+ns}))^2} \tag{11}$$

where ns is the number of sensors and i varies 1 to ns, qe and qs are the experimental and simulated displacements respectively. In this work, it was used two sensors in each bearing, so ns is equal to four that totalizes eight objective functions.

The NSGA II, MOFA and MOPSO parameters can be seen on Tab. 1. The population size and the number of generations (or iterations) are the same for NSGA II and MOFA because they presented the same significance in the algorithms. These parameters represent the number of possible solutions and number of iterations of algorithm respectively, and the product of them is the number of evaluation of the objective functions. The others parameters of NSGA II is the probability of crossover and mutation. The MOFA also considers the randomization parameter, light absorption coefficient and the maximum attractiveness. For MOPSO, the number of iterations and population size is twice the other methods, because the convergence is not achieved when used the same values. The other MOPSO parameters presented are the inertia weight, individuality or cognitive factor and sociability factor.

Table 1 – Search methods parameters.

Algorithms Parameters					
Multi-Objective Genetic Algorithm		Multi-Objective Firefly Algorithm		Multi-Objective Particle Swarm	
Population Size	100	Population Size	100	Population Size	200
Number of Iteration	1000	Number of Iteration	1000	Number of Iteration	2000
Probability of Mutation	0,2	Randomization Parameter	0,4	Inertia Weight	1-5
Probability of Crossover	0,95	Light Absorption Coefficient	4,0	Individuality or Cognitive Factor	2,05
		Maximum Attractiveness	1,0	Sociability Factor	2,05

In the end of all iterations at the algorithms, a set of solutions are reached for each method. This set of data represents the solutions (unbalance moment, phase and position) that minimize the objective functions of Eq. (10) and Eq. (11), and consequently the difference between the experimental and simulated model. However, the choice to the best response is a high order decision. Thus, it was proposed a method of selection: the solutions are separated in groups that take in to account the proximity between them, as shown Fig. 3. After that, it was used the maximum likelihood method, considering a normal distribution with probability density function *pdf* represented by Φ for each objective function. Therefore, the solution with higher likelihood function L (Eq. (12)) has a higher probability to be a better solution. The bests results for each group and the respectively likelihood function L are represented in Tab. 2.

$$L = \prod_{i=1}^{2ns} \Phi(f_i) \tag{12}$$

Figure 3 presents the solutions achieved after application of search methods. For each method, the Pareto set was separated in groups considering the proximity between each element. Besides, each element is represented by different colors and formats to illustrate each method and group. The target solution (based on the experimental test) is also represented in this figure by a black square, with unbalance moment of $1.425{\cdot}10^{-4}$ kg·m, unbalance phase equal to 0 radians and axial position corresponded by the node 8.

Considering the results presented in Tab. 1, it is possible affirm that the three methods were able to find solutions close to expected value. For unbalance moment, there is a tolerable range between $1.1.10^{-4}$ and $1.8.10^{-4}$ and for the unbalance position the nodes 8, 9 and 10, which are the nodes belonged to the disc. A feasible value for the phase angle is around zero radian. The NSGAII presented a time to convergence smaller than others methods did. In this case, with 500 iterations was possible obtain a good convergence of solutions. MOPSO was not able to reach a good convergence of non-dominated solution with the same population size and number of iterations. Thus, these parameters were increased to a population size of 200 possible solutions and 2000 iterations. In this case, a satisfactory solutions set was obtained. For MOFA, the convergence was achieved with 1000 iterations and population size of 100. The size of Pareto set is defined previously for NSGA II. On the other hand, MOPSO and MOFA individuals (possible solution) are guided by the best solutions found at each iteration. Therefore, its Pareto set can reach any size, and for the problem studied, their size was always lower than the NSGA II Pareto set size.

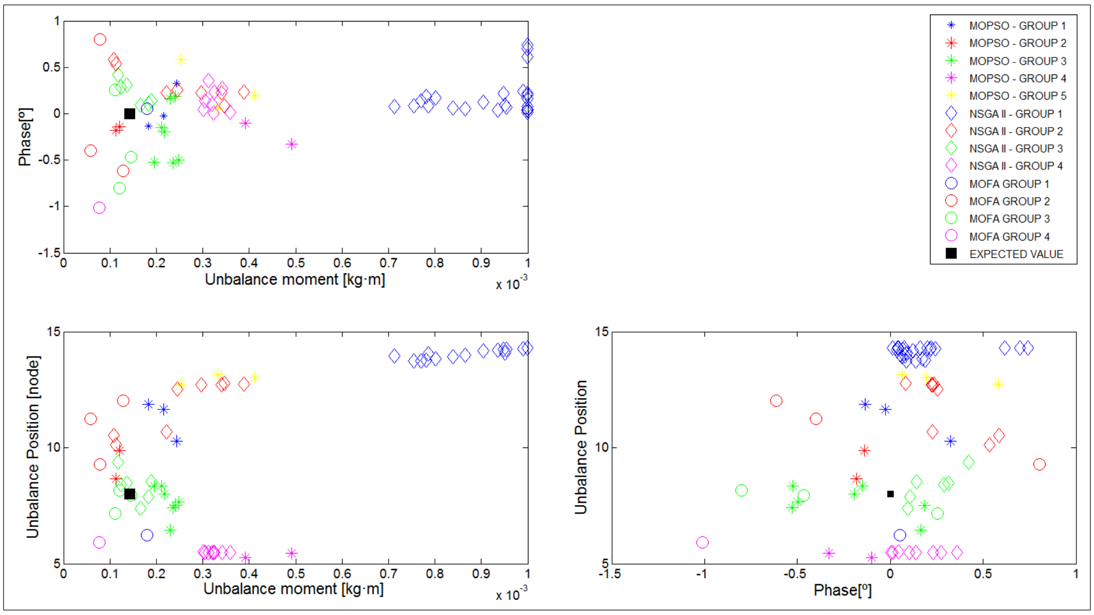

Figure 3 – Groups of solutions to each search methods.

Table 2 – Best solutions for each method separated by group according to maximum likelihood function value.

			Bests Individuals by Group				
			GROUP 1	GROUP 2	GROUP 3	GROUP 4	GROUP 5
NSGA II	X (Solution)	Unbalance Moment [Kg.m]	7,542E-04	1,135E-04	1,240E-04	3,011E-04	-
		Unbalance Phase [°]	0,089	0,534	0,290	0,042	-
		Unbalance Position [Node]	13,741	10,136	8,414	5,499	-
		Maximum Likelihood Function Value [10-4]	6,4162389078	6,4162389061	6,4162389077	6,4162388983	-
MOFA	X (Solution)	Unbalance Moment [Kg.m]	1,795E-04	1,295E-04	1,462E-04	7,711E-05	-
		Unbalance Phase [°]	0,052	-0,614	-0,466	-1,013	-
		Unbalance Position [Node]	6,217	12,018	7,952	5,929	-
		Maximum Likelihood Function Value [10-4]	6,4162389072	6,4162389048	6,4162389067	6,4162389017	-
MOPSO	X (Solution)	Unbalance Moment [Kg.m]	1,834E-04	1,205E-04	2,113E-04	3,912E-04	3,319E-04
		Unbalance Phase [°]	-0,134	-0,141	-0,152	-0,098	0,064
		Unbalance Position [Node]	11,868	9,886	8,363	5,251	13,147
		Maximum Likelihood Function Value [10-4]	6,4162389073	6,4162389082	6,4162389063	6,4162388935	6,4162389025

In order to compare to the simulated model with bests results found by the methods the experimental model, Fig. 4 presents the unbalance response (amplitude and phase) on bearing 2. The blue line represents horizontal displacement y and the red line the vertical displacement z. The unbalance parameters used for the comparison was the group 3 of NSGA II and GROUP 2 of MOPSO, where a good accuracy is presented between the optimized solution and the experimental test. In both case, the node is located on the disc and the unbalance mass and phase are close to the expected value

6. CONCLUSION

This paper is a comparison between multi-objective methods NSGA II, MOFA and MOPSO to find fault parameters (unbalance moment, phase and axial position) of a rotating system.

Objective functions used to find these fault parameters are representations of the difference between the model and experimental response for each sensor that are located on each bearing.

All methods were able to find satisfactory solutions that are close to the value expected. There are some values more distant to expected response that were considered part of the Pareto set, but in real cases, they are not feasible.

The NSGA II was the faster method and with more diversity because is a commercial computational tool, presented in MATLAB toolbox. Although MOFA resulted in few solutions and concentrated on a limited localization, they are satisfactory values. MOPSO was the method with high computational cost, because it was necessary more objective function evaluations. Therefore, improvements can be implemented to MOFA and MOPSO, by an analysis and consequently better selection of methods parameters.

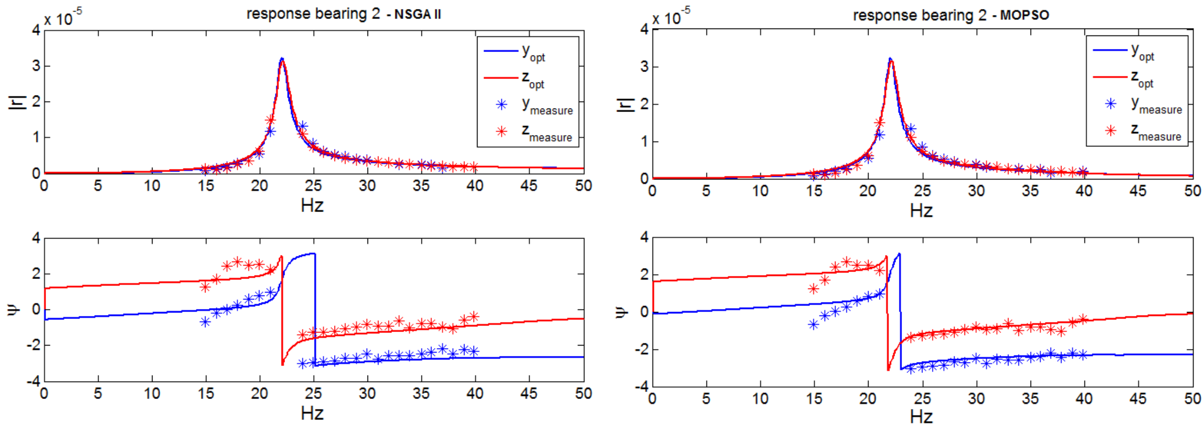

Figure 4 – Unbalance response to NSGA II and MOPSO

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8. RESPONSIBILITY NOTICE