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PARAMETER IDENTIFICATION OF FLEXIBLE STRUCTURES USING HEURISTIC OPTIMIZATION METHODS

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Abstract. *The Finite Element models provide accurate results, however in experimental applications it is possible to notice a significant difference between the analytical predictions and the experimental results. This difference may be related to uncertainties in the geometry configuration, inappropriate material parameters, and inaccurate boundary conditions. In order to cope with this drawback, several studies have dealt with the solution to the inverse problems embedded in the updating of Finite Element models. Therefore, this paper presents an evaluation of three heuristic optimization methods, the Differential Evolution, the Genetic Algorithm and the Particle Swarm. They are used to fit the Finite Element models of flexible structures. The influence of the initial population size is analyzed for each optimization methods. In the end, the results showed the efficiency of the methods.*

Keywords: *flexible structures, model fitting, heuristic optimization methods, inverse problems*

1. INTRODUCTION

In mechanical engineering, when it comes to designing new equipment, it is necessary that the designer attempts to develop an equipment with low transmissions of vibration and noise levels within the operation range, given that they are undesirable and degrade the equipment’s life, increasing costs and even others problems that could be avoided if it had been done a better study and planning in the design phase. Nowadays, a product must have some essential characteristics, such as durability, safety and low production cost. Specifically, for rotor dynamics, it isn’t different, since there are several ongoing studies in order to improve the mathematical models and to enable the consideration of typical characteristics and material’s properties of the flexible rotors so that it is possible to reduce the vibrations and improve its performance. (Lalanne and Ferraris, 1998)

In order to get a rotor model it is necessary to consider several subsystems. These subsystems are defined by their geometry, such as shaft and disc coupling, and also there are the subsystems that are frequency or dependent state, such as bearing and Coriolis Effect. The parameters are identified by using the inverse problem. The solution of the inverse problem can be obtained using optimization methods, here, it may be mentioned several methods, such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE) and others. In this paper, those three methods were used and their results compared while the population size is varying.

2. FLEXIBLE ROTOR

Through the Hamilton’s Principle, the mechanical system dynamic response can be modeled. For this purpose, it is necessary to calculate the shaft’s strain energy and its kinetic energy and the disk’s kinetic energy. Using the Hamilton’s Principle, it is possible to include the effect of energy dissipation. The bearing parameters are considered in the system model by the principle of virtual work. For discretization of the structure, it is used the finite elements method, thus the calculated energy are concentrated in the nodal points. Shape functions were used to connect the nodal points. The shaft stiffness is obtained by means of the Timoshenko’s beam theory and the cross-section area was updated. The obtained model is represented mathematically by a set of differential equations according to Lalanne and Ferraris (1998) as given by Eq. (1) in a matrix form.

$$[M]\{\ddot{x}(t)\}+\left[[C_b]+\dot{\phi}[C_g]\right]\{\dot{x}(t)\}+\left[[K]+\ddot{\phi}[K_g]\right]\{x(t)\}=\{F_U(t)\} \tag{1}$$

Where, $\{x(t)\}$ is the generalized displacement vector; [M], [K], $[C_b]$, $[C_g]$, and $[K_g]$ are the well-known inertial matrix, stiffness, viscous damping bearing, gyroscopic, and the effects of varying the rotational speed, $\dot{\phi}$ is the angular velocity that vary with time, and $\{F_u(t)\}$ is the unbalanced force. Figure 1 shows the discretized model of the analyzed rotor.

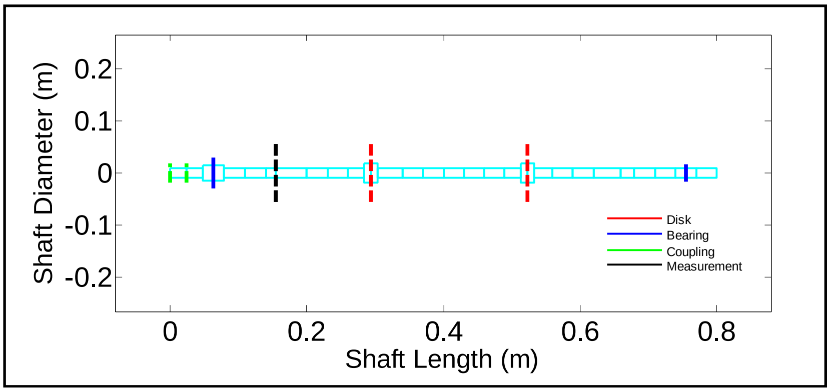


Figure 1. Discretized model. (Koroishi, et al. 2014)

The nodes 4 and 31 correspond to the bearing, the nodes 8 and 27 correspond to the sensors and the nodes 13 and 22 correspond to the disk position. More details about the rotor can are reported by Koroishi, et al. (2014).

3. HEURISTIC OPTIZATION METHODS

Optimize means improve something that already exists (Lobato, 2008), thus, the optimization tries to improve the system configuration, although it has its limitations, some of those are: the increase in the computational time when the design variables increase, the appearance of discontinuous function that converge slowly or even function with several minimum local, which makes difficult to find a global minimum. In order to apply the optimization algorithm, it must be taken into account the nature of the objective function, the restriction and the number of the dependent and independent variables.

The objective function defines the system characteristic that must be improved. This characteristic is represented by a mathematic equation dependent on the design variables. These design variables, also known as decision variables, are a set of parameters which may influence the values of the objective function. If the design variables are properly handled, it promote modifications in the values of the objective function. The restrictions limit the values of the objective functions to certain regions of the design space and they are characteristics that mathematically depend on the design variables. (Vanderplaats, 1999)

3.1 Differential Evolution

This method was proposed by Storn and Price in 1995, it is based on evolutionary concepts to find an optimal point (Zou, et al., 2013). It is used vector operation to obtain a new possible candidate to solve the problem. Two vectors ($\mathbf{x}_{r2}$, $\mathbf{x}_{r3}$) are selected randomly among three vectors ($\mathbf{x}_{r1}$, $\mathbf{x}_{r2}$, $\mathbf{x}_{r3}$) in order to subtract them and multiply by a scalar F. This way, it's obtained a vector F($\mathbf{x}_{r2}$ - $\mathbf{x}_{r3}$) that will be added to vector $\mathbf{x}_{r1}$, So a new vector is obtained, $\mathbf{v}_i$, this vector is a new character, which indicates a new position in space. Figure 2 shows a graphical scheme of search for DE algorithm (Lobato, 2008). Figure 3-a shows a flowchart of the DE algorithm.

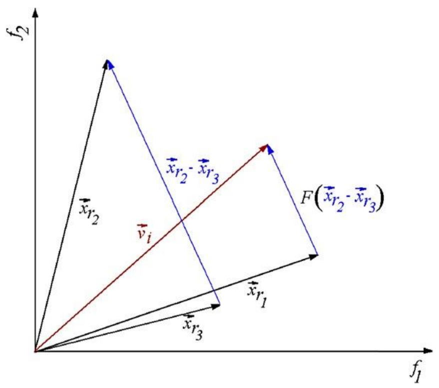


Figure 1. Theorical foundation of DE algortihm (Lobato, 2008).

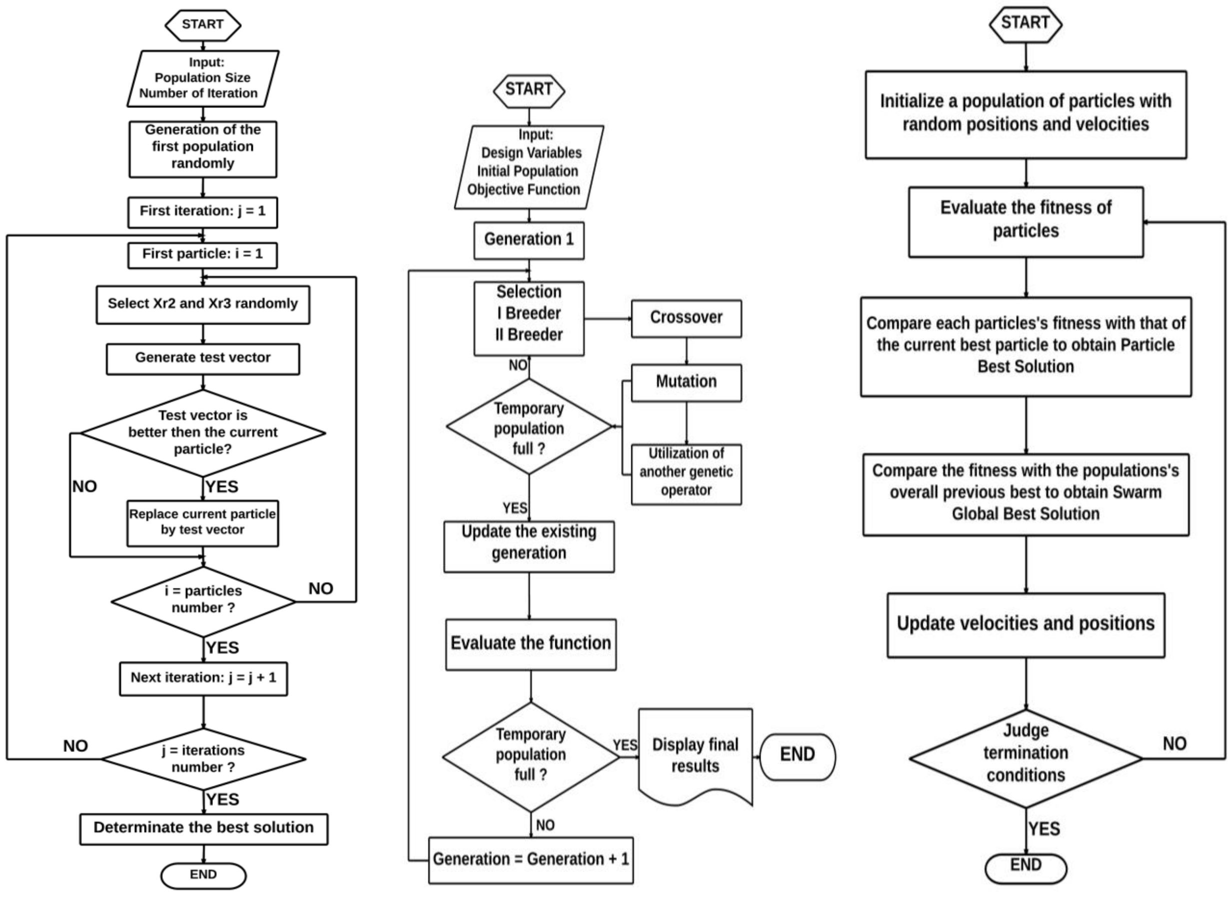
3.2 Genetic Algorithm

This technique was presented firstly by Holland in 1975 and it was extended by De Jong and Goldberg. It is a robust technique that can be applied to several scientific and engineering problems with success (Zhang, et al., 2005). GA doesn't require the solution of differential equations, so, it can work fine in complex problems with discontinuity and discrete function (Saruhan, 2006). According to Lobato (2008), it makes use of biologic operators, as crossing, recombination and mutation to generate better individuals.

Figure 3-b shows flowchart of the GA algorithm.

3.3 Particle Swarm Optimization

This technique was introduced by Kennedy and Eberhart in 1995 and it is based on social behavior of birds. When birds are looking for food around a delimited area, it is supposed that the food will be at a certain location that the birds don't know. So, when one bird finds this food its success is shared with the whole swarm so that, it is learning from the experience of others individuals. The process of PSO uses the memory of each particle and the knowledge obtained by the swarm. Figure 3-c shows a flowchart of PSO algorithm.



(a) (b) (c)

Figure 3. Flowchart: (a) DE (Keshtkar et al, 2011), (b) GA (Saruhan, 2006) and (c) PSO. (Rajendra et al., 2011)

4. COMPUTER SIMULATION

Table 1 shows the data of the rotor model and the bearing, as mass of shafts, mass and thickness of disks, diameter and also the search range for the stiffness (K), damping (C) parameters in the horizontal (x) and vertical (y) directions.

The objective function used, as shown on Eq. (2), had the objective to minimize the differences between the generated FRF through the FE model and those obtained through the model with nominal parameters.

$$S_{fit} = \sum_{n=1}^{N} \left(\frac{\left\| FRF_{ijk}^{exp} - FRF_{ijk}^{sim} \right\|}{\left\| FRF_{ijk}^{exp} \right\|} \right) \qquad (2)$$

Where, S_{fit} is the scores of the objective function, FRF_{ijk}^{exp} are the FRFs obtained from the nominal model and the FRF_{ijk}^{sim} are the ones obtained by the FE model.

Table 1: Physical characteristics of the rotor-bearing system and parameters range.

Characteristic	**Value**	**Bearing**	**Properties**	**Direction**	**Limit**	
Mass of shaft (Kg)	4,1481				**Lower**	**Upper**
Mass of disk D1 (Kg)	2,6495	**1**	**K (N/m)**	**x**	500000	5000000
Mass of disk D2 (Kg)	2,6495			**z**	500000	1E+07
Thickness of D1 (m)	0,1		**C (Ns/m)**	**x**	0	200
Thickness of D2 (m)	0,1			**z**	0	200
Diameter of shaft (m)	0,029	**2**	**K (N/m)**	**x**	5E+07	1E+09
Young modulus (GN/m²)	205			**z**	5E+07	1E+09
Density (Kg/m³)	7850		**C (Ns/m)**	**x**	0	200
Poisson coefficient	0,3			**z**	0	200

The design variables are stiffness and damping of the bearings. Six initial population sizes were considered: 50, 100, 150, 200, 250 and 300. The optimizer was run ten times for each population size.

Figures 4, 5 and 6 show the results of the simulation for the three methods. The results are C and K obtained and its variation is represented by the blue box, the red line is the median of the results and the red "+" signal is a result that is too far from the variation.

In the Fig. 4, 5 and 6, the letters (a), (b), (c) and (d) refer to the stiffness and the letters (e), (f), (g) and (h) refer to the damping.

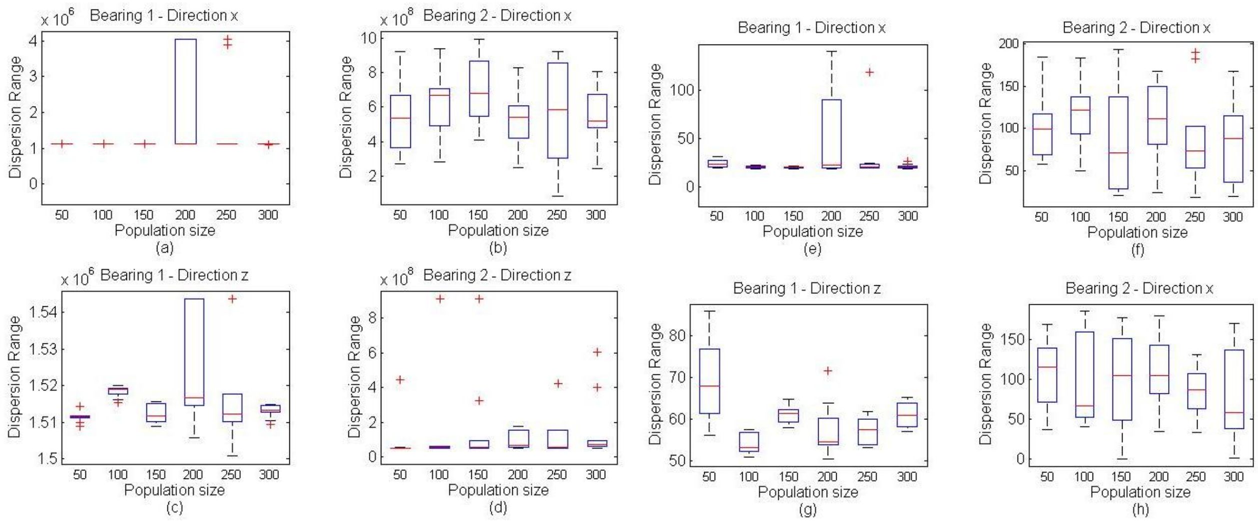


Figure 4. Results of DE simulation for stiffness and damping**.**

Figure 7, 8 and 9 show some FRF from the method DE, GA and PSO, respectively. These graphics present the best results that were obtained by each method. For each method, the better results were obtained with different population size: 50 (DE), 100 (GA) and 150 (PSO).

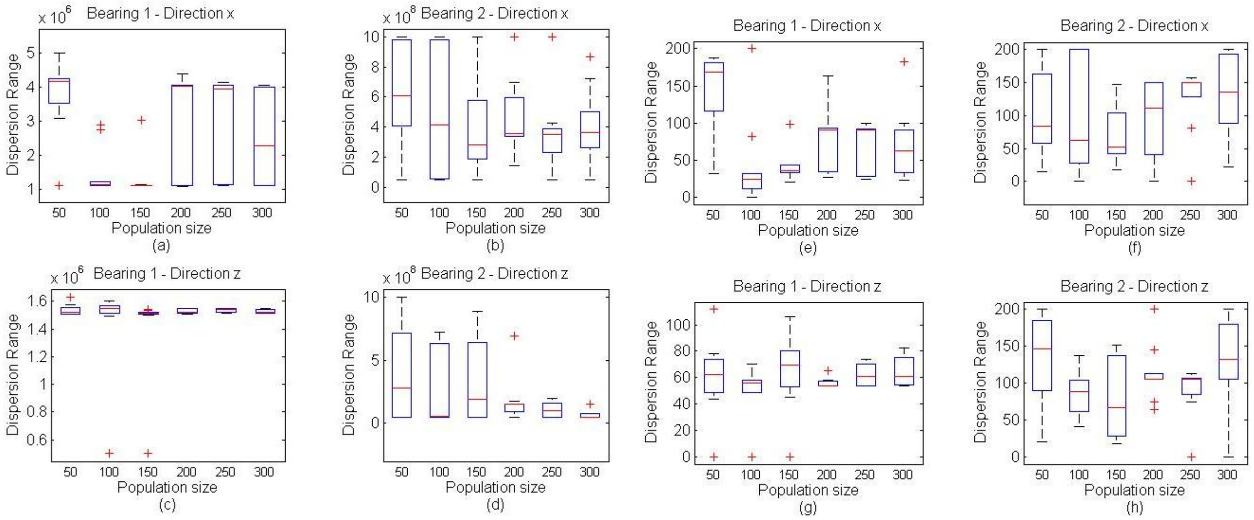


Figure 5. Results of GA simulation for stiffness and damping.

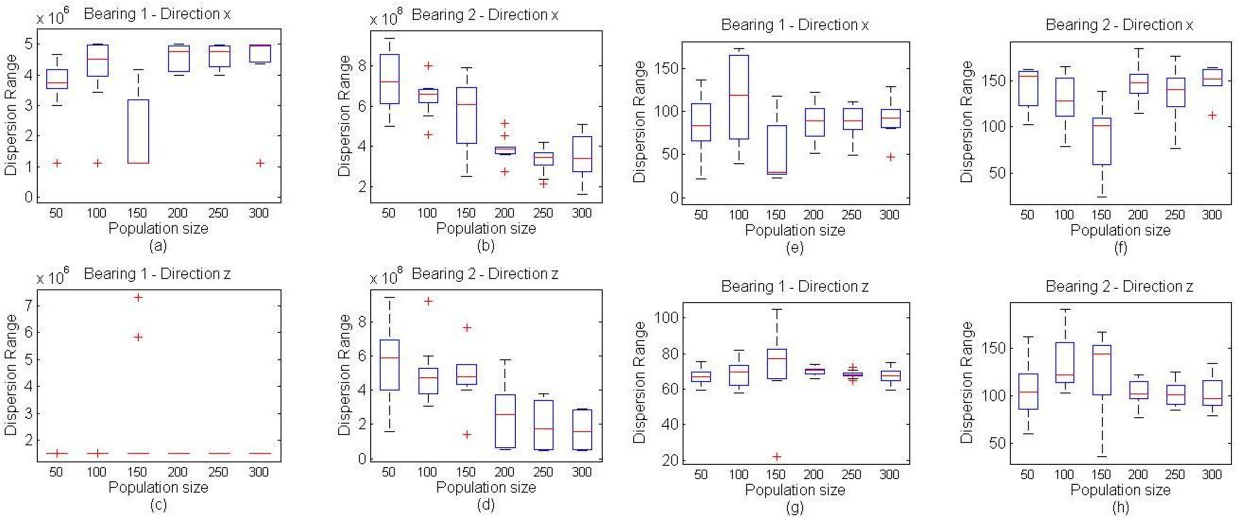


Figure 6. Results of PSO simulation for stiffness and damping.

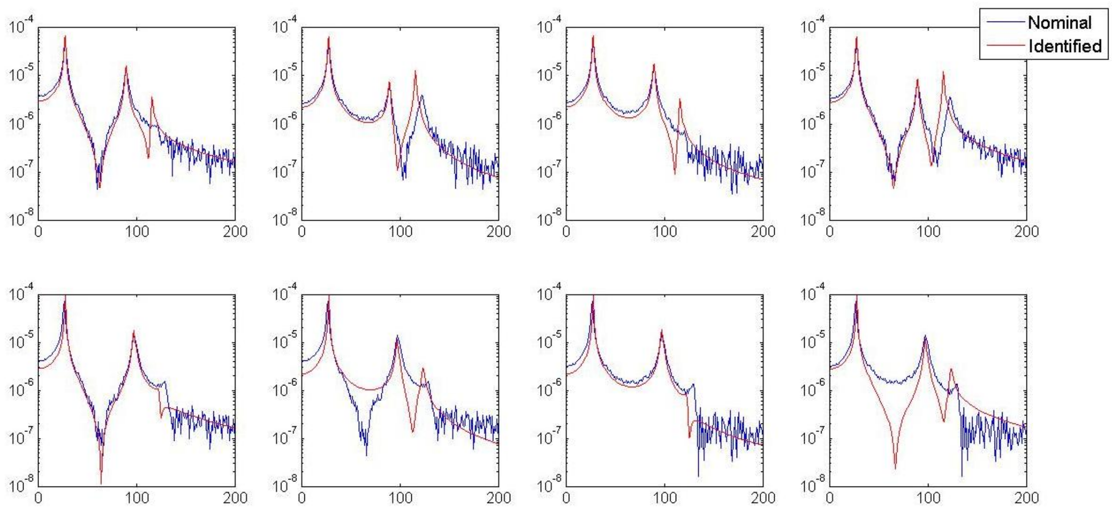


Figure 7. DE Population Size 50.

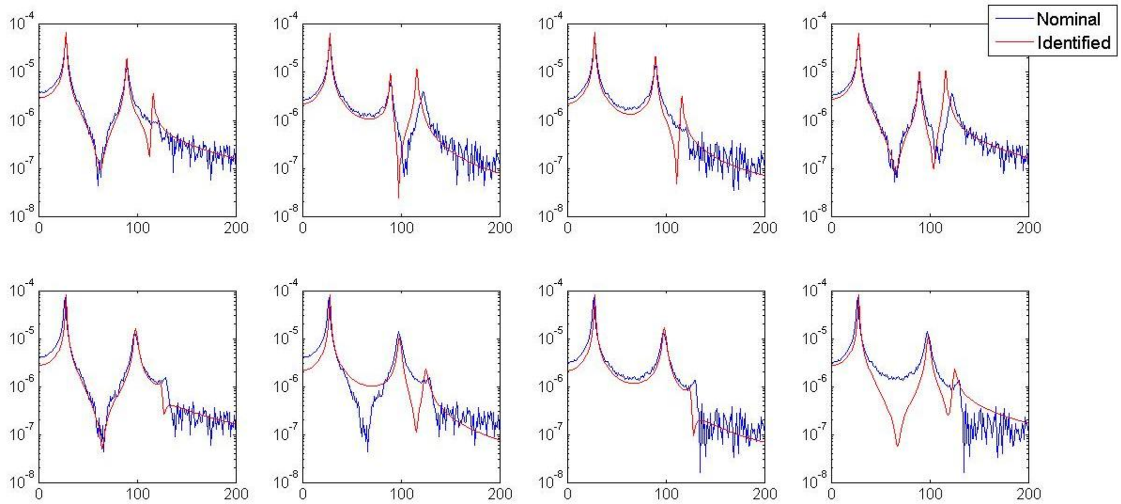


Figure 8. GA Population Size 100.

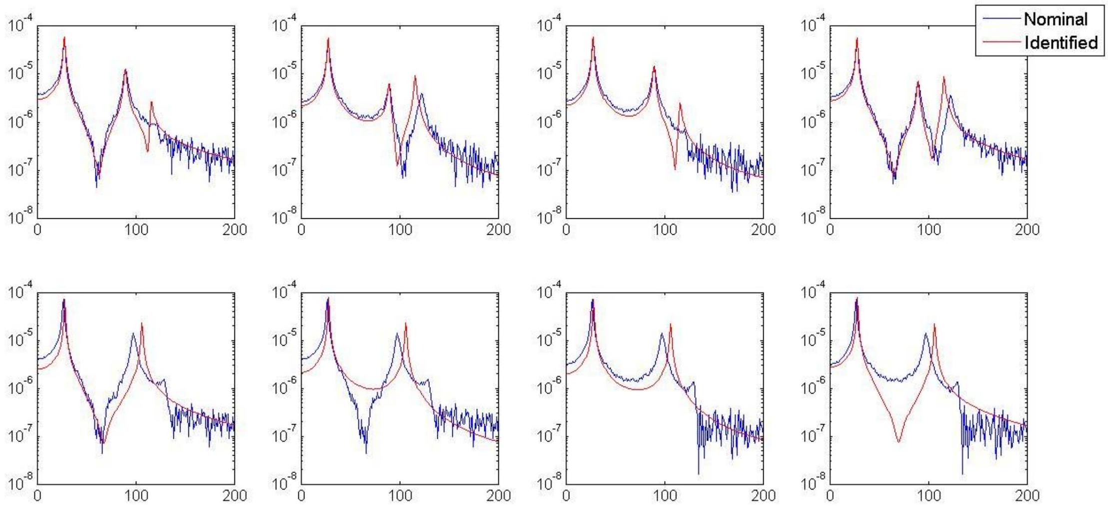


Figure 9. PSO Population Size 150.

For these populations, the FRFs identified from DE and GA are really close but it is possible to notice that, in some FRFs identified from PSO, the peak didn't match with the nominal. This doesn't mean that the obtained results are wrong, these results should be a local minimum and not a global minimum.

Table 2 shows the values of the parameters identified used to obtain the FRFs presented in Fig. 7, 8 and 9.

Table 2: Parameters identified by performing the techniques.

Bearing	**Properties**	**Direction**	**Value identified**		
			DE	**GA**	**PSO**
1	**K (N/m)**	**x**	1112408,054	3034812,097	4050630,155
		z	1518829,051	1516711,536	1543686,205
	C (Ns/m)	**x**	21,185826	98,35219366	163,902752
		z	56,78804813	80,41946099	53,97673274
2	**K (N/m)**	**x**	676496109,4	328581492,7	351941401
		z	51013369,02	641696013,2	50000000
	C (Ns/m)	**x**	122,4529509	57,95925831	30,38679819
		z	165,4277942	109,1417373	104,9274691

The results presented by Tab. 2 demonstrate that the identified values of stiffness and damping show different values. It is important to say that, when heuristic optimization technique was used, the optimization searched for the best result to satisfy the objective function, and consequently, the values in Tab. 2 become different for each method.

5. CONCLUSIONS

The results presented by this paper demonstrate that these techniques work to fit the FE models of flexible structures. They were able to solve the inverse problem and identify the unknown parameters.

Even for a low population size, which implies in a low computational cost, the parameters were identified, and the variation of the population size seemed to have a small influence in the result, perhaps, for better analysis it would be necessary to run the optimizer more times, this way, it would be possible to have more accurate answers.

Generally, the results presented by the three methods were satisfactory since all of them achieved the objective, that was identify the unknown parameters, K and C. Comparing Fig. 4, 5 and 6, it is possible to notice that DE obtained better results to find the stiffness and damping because the variation in the boxplot was smaller than for the other two methods, in other words, it had a better convergence. GA also achieved good results with a good convergence. Among the three methods PSO achieved results not so good as the others, but it is considerable yet.

6. ACKNOWLEDGEMENTS

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