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UPDATING METHOD BASED ON MULTI-OBJECTIVE GENETIC ALGORITHM METHOD APPLIED TO NON-LINEAR JOURNAL BEARING MODEL

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Abstract. *The present work proposes a multi genetic algorithm to fit dynamic parameters of rotors. A non-linear journal bearing model is analyzed and adopted to adjust the unknown parameter. This analysis shows that the proposed bearing model is in agreement with known linear bearing models. To validate the fitting method, a simulated fitting process was accomplished. The fitting results are satisfactory, but the applied computational resources are considerable elevate.*

Keywords*: Journal bearing, Non-linear model, Model Updating, Genetic Algorithm*

1. Introduction

The rotordynamic analysis is becoming a previous phase of study to the design, due to the possibility of predicting problems during the operation of the system, as those caused by vibration amplitudes when a rotor, for example, is passing through a critical speed (Lalanne, 1990 and Vance, 1988).

Mathematical models were developed, in order to represent real machines with considerable confidence. So, several researches were pointed to determine better models to rotating machinery as turbogenerators and multi stage pumps, which are horizontal rotating machines of high loads capacities. Some of these numeric simulations were developed to study cylindrical hydrodynamic bearings by Capone (1991 and 1986), where the orbits of the shaft in the bearings can be obtained.

The experimental analysis is also a strong support in processes of predictive and preventive maintenance, because allows the diagnosis of operational problems, before some failure of the system. This work makes use of non-linear models to the hydrodynamic bearing analysis (Cavalca, 1994 and 1998), through the evaluation of the hydrodynamic oil film resultant forces. The supporting hydrodynamic forces model adopts the short bearing mathematical development (Childs, 1993). From this approach, it is possible to obtain faster numerical solutions of the motion equations of the system. Experimental data can be utilized to update analytical model and estimate or improve unknown parameters. Irretier and Liedermann (2002) improved damping parameters from experimental results and model updating.

Cavalca et al. (2001) proposed an unrestricted optimization method to updating non-linear journal bearing forces model to experimental results. This fit method was limited by an unique parameter for each bearing, the temperature, which influences the viscosity of the oil film in the bearings. These parameters incorporated all the non simulated effects, as the coupling stiffness, the oil flux in the bearings, different torques in the screws assemble of the joining, etc. Therefore, the adjusted parameter, in certain situations, did not converge to physical meaning values.

In this work a multi-parameter method is used to update the model. The method is based on genetic algorithm (GA) that is a metaheuristic search method that simulates a biological reproduction and evolution through generations (iterations). It is a robust method, because it is not influenced by local optimum or signal noise. It is not necessary to use differential calculus or any kind of advanced mathematical concept as well. The genetic algorithm was applied to model updating or refinement by Levin (1998) and Zimmerman (1998).

2. Mathematical Model

A mathematical model of a rotating system can be divided in two parts; the finite element model of the shaft and the concentrated mass to the disk, and the non-linear hydrodynamic supporting forces of the cylindrical journal bearing, which is obtained by the Reynolds' equation solution for short bearings.

Equation (1) describes the pressure distribution inside the cylindrical journal bearing, based on the Reynolds' equation solution for laminar flux condition. This expression considers the oil thickness *h* and the axial gradient *z*, due to the losses of lubricating fluid in short journal bearing.

$$\frac{\partial}{\partial \upsilon}\left(h^3.\frac{\partial p}{\partial \upsilon}\right)+k^2.\frac{\partial}{\partial z}\left(\frac{h^3}{\mu}.\frac{\partial p}{\partial z}\right)=\frac{\partial h}{\partial \upsilon}+2.\frac{dh}{d\tau} \qquad (1)$$

The pressure gradient in circumferential direction can be neglected for short journal bearing in relation to the axial gradient (Childs, 1993). Therefore, the result of the differential equation with this simplification is:

$$p(\upsilon,z)=\frac{1}{2}.\left(\frac{L}{D}\right)^2.\left[\frac{(x-2.\dot{y}).\sin(\upsilon)-(y+2.\dot{x}).\cos(\upsilon)}{\left(1-x.\cos(\upsilon)-y.\sin(\upsilon)^3\right)}\right].\left(4.z^2-1\right) \qquad (2)$$

In order to determine the force generated by the oil film pressure distribution, the shaft contact area, $dA = R.d\upsilon.L.dz$, is considered in Eq. (3):

$$Fh=\begin{Bmatrix}Fh_x\\ Fh_y\end{Bmatrix}=-\mu\omega\left(\frac{R^2}{C^2}\right)\left(\frac{L^2}{D^2}\right)(R.L)\frac{\left[(x-2\dot{y})^2+(y+2\dot{x})^2\right]^{\frac{1}{2}}}{(1-x^2-y^2)} .\begin{Bmatrix}3xV(x,y,\alpha)-\sin(\alpha)G(x,y,\alpha)-2\cos(\alpha)F(x,y,\alpha)\\ 3yV(x,y,\alpha)-\cos(\alpha)G(x,y,\alpha)-2\sin(\alpha)F(x,y,\alpha)\end{Bmatrix} \qquad (3)$$

Where the terms *V, G* and *F* are respectively given in Eq. (4), (5) and (6).

$$V(x,y,\alpha)=\frac{2+(y.\cos(\alpha)-x.\sin(\alpha)).G(x,y,\alpha)}{(1-x^2-y^2)}. \qquad (4)$$

$$G(x,y,\alpha)=\int_{\alpha}^{\alpha+\pi}\frac{d\upsilon}{(1-x.\cos(\upsilon)-y.sen(\upsilon))}=\frac{\pi}{\sqrt{1-x^2-y^2}}-\frac{2}{\sqrt{1-x^2-y^2}}.arctg\left(\frac{y.\cos(\alpha)-x.\sin(\alpha)}{\sqrt{1-x^2-y^2}}\right) \qquad (5)$$

$$F(x,y,\alpha)=\frac{(x.\cos(\alpha)+y.\sin(\alpha))}{(1-x^2-y^2)} \qquad (6)$$

The differential equation of motion must be written in two coordinates, *x* and *y*, respectively Eq. (7) and (8).

$$[M].\frac{d^2x}{dt^2}+([C]+[G]).\frac{dx}{dt}+[K].x=Fh_x(x,y,\frac{d}{dt}x,\frac{d}{dt}y)+\omega^2.M.E.\cos(\omega.t) \qquad (7)$$

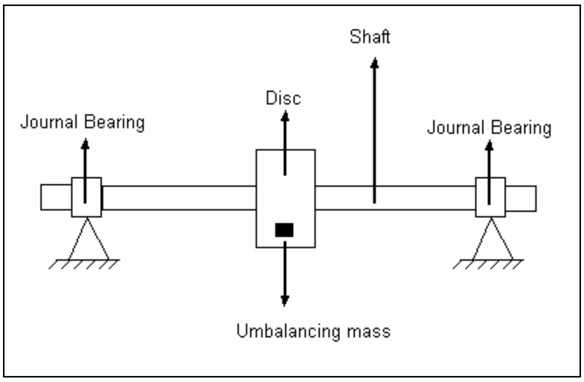
$$[M].\frac{d^2y}{dt^2}+([C]+[G]).\frac{dy}{dt}+[K].y=Fh_y(x,y,\frac{d}{dt}x,\frac{d}{dt}y)+\omega^2.M.E.\sin(\omega.t)-W \qquad (8)$$

The matrixes *[M], [C], [G]* and *[K]* are respectively the mass, damping, gyroscopic and stiffness matrixes of the shaft and concentrated mass, which are obtained by a classical finite element method. The shaft damping matrix *[C]* is considered as proportional to the stiffness and mass matrixes ([C] = α[M] + β[K]). The rotor weight is represented in these equations by *W*.

The solution of the equation of motion is obtained by the application of numerical methods. In that case, the Newmark integration method was chosen, because it is a robust algorithm to solve non-linear equations in time domain.

3. Simulated Results

In order to simulate the rotor system, the model represented by Fig. 1 was adopted. The model parameters is also shown in Fig. 1



Proportional coefficient related to stiffness β	$25 \cdot 10^{-6}$
Proportional coefficient related to mass α	15
Weigh of the disc	20.95148 kg
Young's Modulus of the shaft	$2.067 \cdot 10^{11}$ Pa
Shaft density	7800 kg/m^3
Shaft length	690 mm
Shaft diameter	12 mm
Shaft diameter in the bearings journal	20 mm
Bearing diameter	20 mm
Bearing length	20 mm
Oil viscosity	60 mPa.s
Bearing clearance	180 µm
Unbalance Moment	$5 \cdot 10^{-4}$ kg.m

Figure 1 – Simulated model and model parameters

Considering the parameters of Fig. 1, the dynamic system was simulated. The responses of this simulation are shown in Fig. 2 to 7.

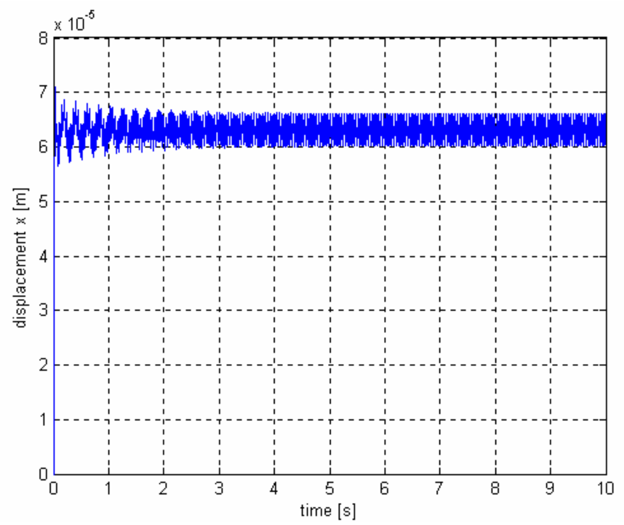


Figure 2 – Displacement x of simulated system x time

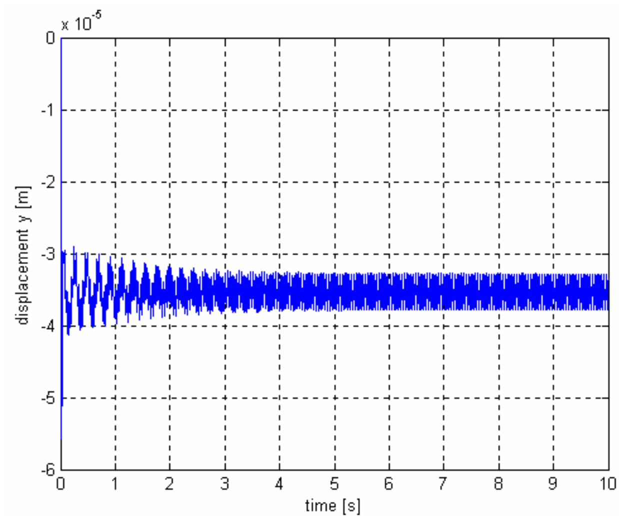


Figure 3 – Displacement y of simulated system x time

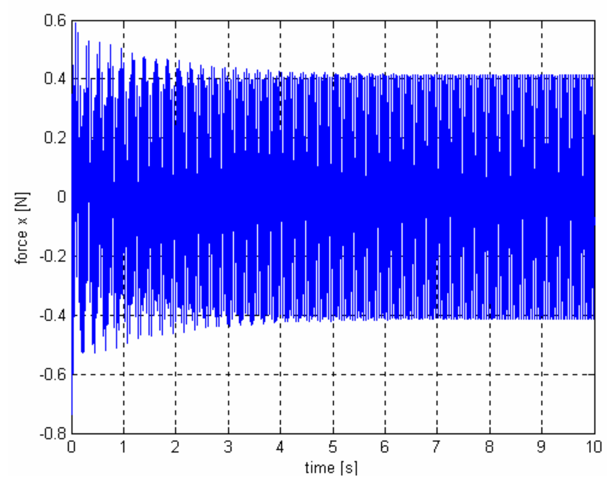


Figure 4 – Hydrodynamic Force x of simulated system x time

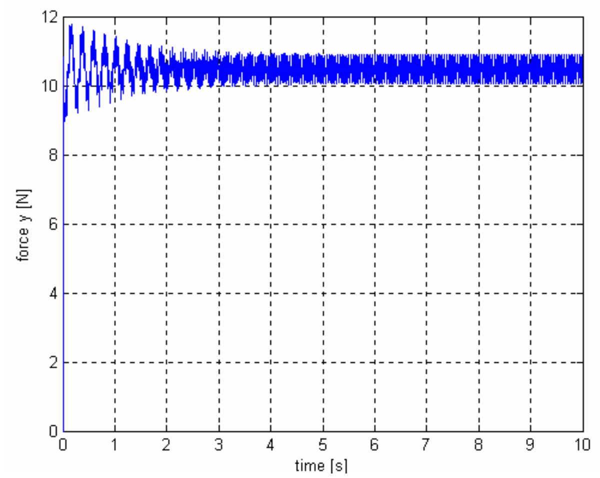


Figure 5 – Hydrodynamic Force y of simulated system x time

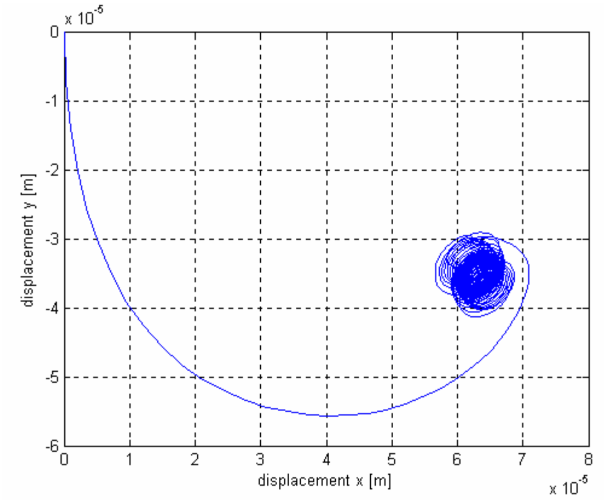


Figure 6 – Orbit of the System (Transient + steady state)

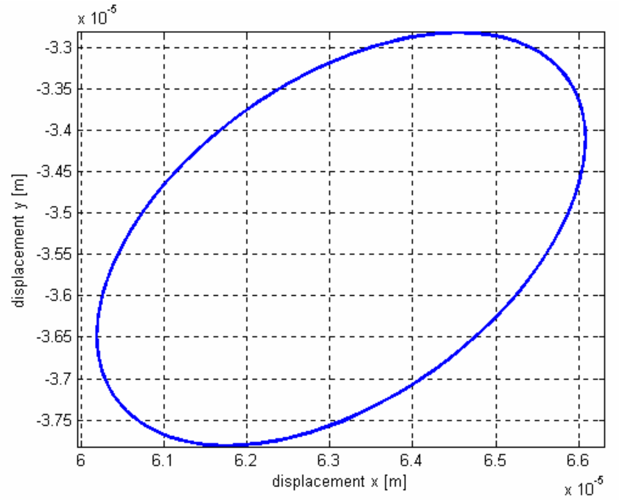


Figure 7 – Orbit of the System (Steady State part)

It can be noted that the mean force in the y axes (Fig. 4) is the half of the weigh of the system, because there are two bearing in the system.

To verify the influence of rotational speed, disc weight, unbalance moment, oil viscosity and bearing clearance, the system was simulated varying these parameters. Figures 8 to 11 show these influences on the orbit of the shaft center in the bearing. It is also possible to observe the change in the position of the shaft center in the bearing.

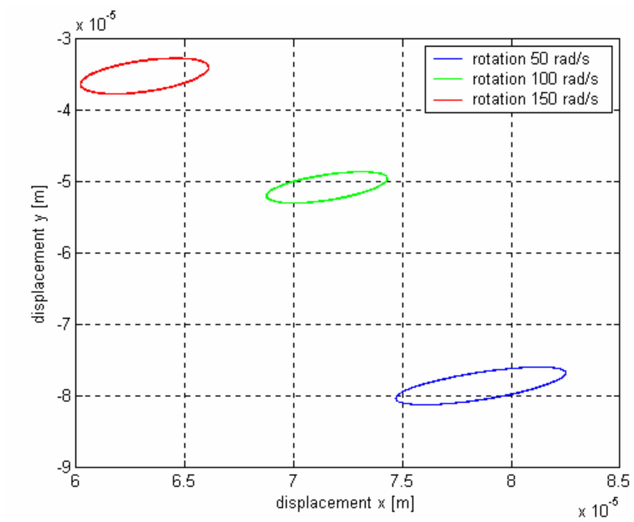


Figure 8 – Rotation speed influence

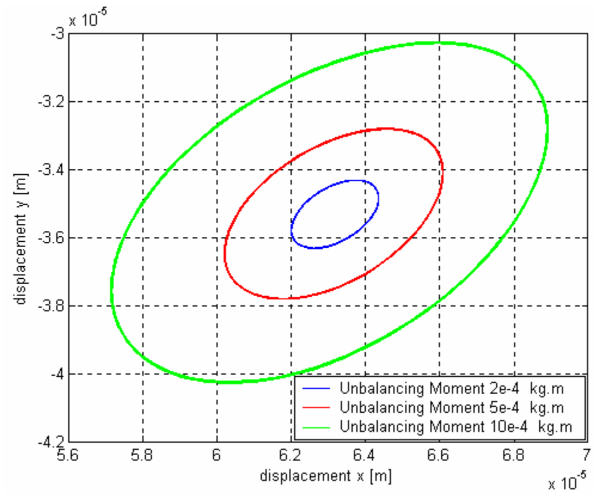


Figure 9 – Unbalance Moment influence

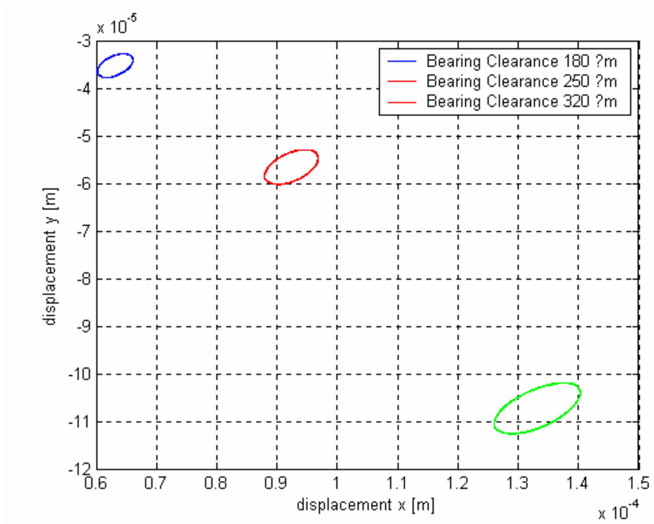


Figure 10 – Bearing Clearance influence

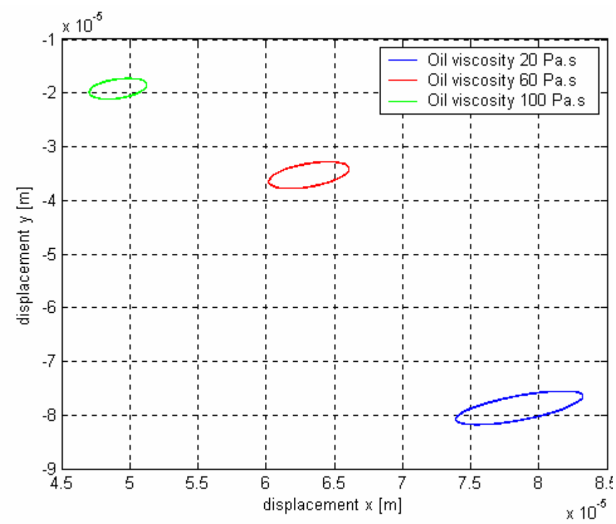


Figure 11 – Oil viscosity influence

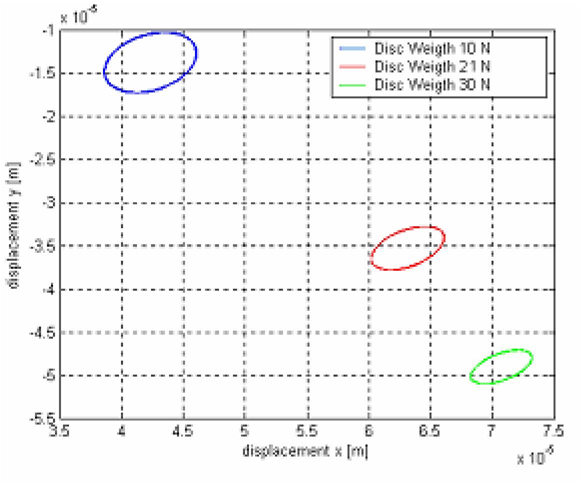


Figure 12 – Disc weight influence

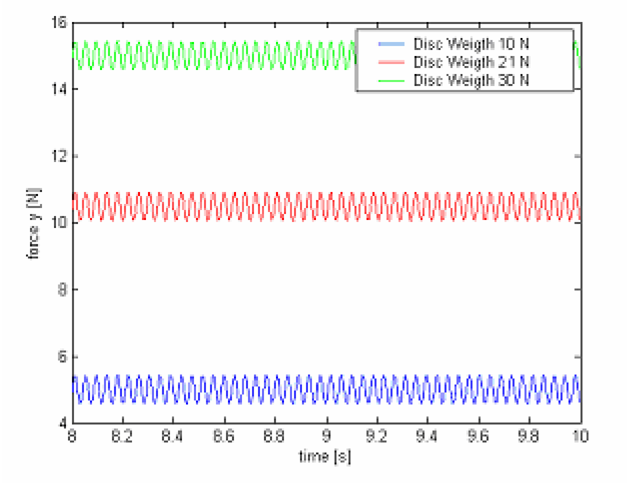


Figure 13 – Disc weight influence in force y

If the rotational speed increases, the center of the shaft approaches to the center of the bearing, as in Fig. 8. The unbalance moment does not change the position of the shaft (Fig. 9), but it strongly influences the orbit amplitude. As observed in Fig.10, the bearing clearance increases causes higher orbits and the center of shaft move away from the bearing center. A higher viscosity (Fig. 11) decreases the amplitude of the oscillation and the shaft approaches the bearing center. As it is expected, a weightier disc changes the mean force in y axes (Fig. 13) and increases the eccentricity position (Fig. 12).

Some of these parameters cannot be known in physicals systems. So, it is necessary fitting methods to adjust these parameters. This work proposes a fitting method based in a multi-objective genetic algorithm. The fitted functions are the bearing and disc orbit and hydrodynamics forces.

4. Genetic Algorithm

The genetic algorithm is a search strategy that employs random choice to guide a highly exploitative search, striking a balance between exploration of the feasible domain and exploitation of "good" solutions (Holland,1992). This strategy is analogous to biological evolution. From a biological perspective, 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 recombination. 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.

The decoding of a binary sequence to decimal number (integer or real) is represented by Eq. (9):

$$x_j = c_j + \sum_{i=0}^{k-1} b_i \cdot 2^i \cdot \frac{d_j - c_j}{2^k - 1} \tag{9}$$

Where c_j and d_j are the maximum and minimum possible values of the decimal variable x_j and b_i are the digit ith of a binary number with k digits.

Thus, the number of digits of an individual (chromosome) is the product of the number of variables and the number of bits.

Members of a population are subjected to operators in order to create offspring. Commonly used operators include selection, reproduction, 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 reproduction, 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. 14 represents these two operators.

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

The size of binary string in the implemented genetic algorithm is equal to the product of the number of variables and the number of bit of each variable. The problem variables are unbalancing moment and the viscosity of each journal bearing, so it is equal to three. The number of bit of each variable is eight. Consequently, the size of the string is twenty four.

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.
- 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 value of 10% of individuals are kept in the next generation. This process is known as elitist strategy and this rate is also a genetic algorithm parameter.

Figure 15 shows the genetic algorithm flowchart and its steps from the generation of initial population to the end of the search process.

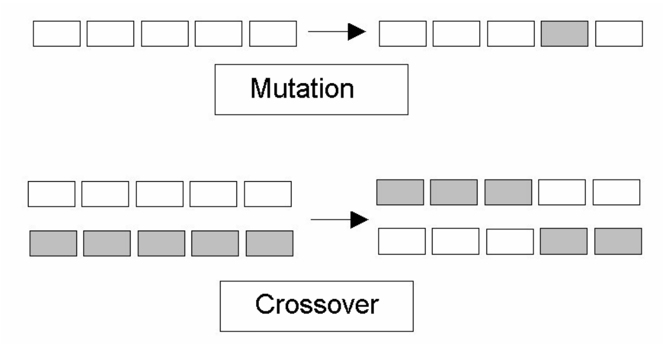


Figure 14 – Mutation and Crossover

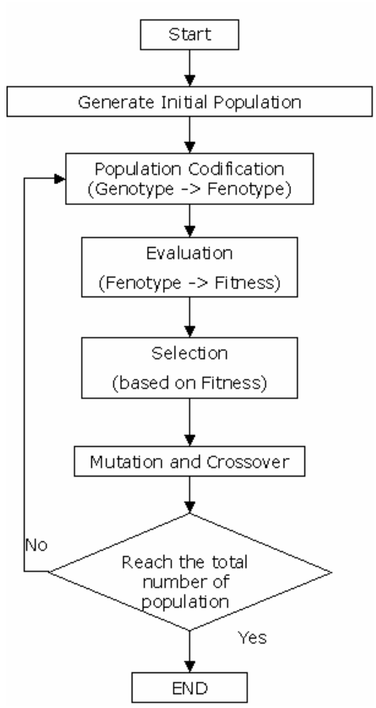


Figure 15 – Genetic Algorithm Flowchart

5. Objective Function

The GA works with an objective function, containing all the control variables. That function correlates the experimental (or simulated) information with the adjusting variable values, which determines the error function. The objectives functions considers average of *x* and *y* displacements in both bearings and in the mass displacement for experimental and adjusted data. The variable *w* is the weight of the objective function, equal to 0.2 for this case. This weight can group all functions in a single one (Eq. 10).

$$fo = \sum_{bearing}\left(w_{bearing}\frac{\left| X_{bearing}^{adjusted} - X_{bearing}^{\text{experimental}} \right|}{X_{bearing}^{experimental}} + w_{bearing}\frac{\left| Y_{bearing}^{adjusted} - Y_{bearing}^{\text{experimental}} \right|}{Y_{bearing}^{experimental}} \right) + \sum_{mass}\left(w_{mass}\frac{\left| X_{mass}^{adjusted} - X_{mass}^{\text{experimental}} \right|}{X_{mass}^{experimental}} + w_{mass}\frac{\left| Y_{mass}^{adjusted} - Y_{mass}^{\text{experimental}} \right|}{Y_{mass}^{experimental}} \right) \quad (10)$$

The adjustment process uses three variables, which are the variation of the unbalance moment and viscosities in both bearings. They are the Finite Element Model of rotor input, where the results (orbits) are used in the objective function to determine the error value, returning to the GA (Fig. 16). The parameter variation law is given by the Genetic Algorithm Method.

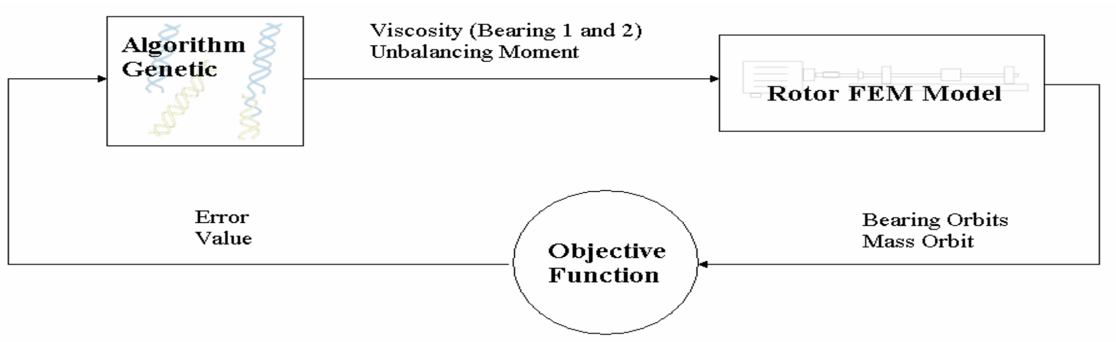


Figure 16 – Adjustment process using a rotor model, objective function and genetic algorithm method.

6. Simulated Fitting

A Laval rotor supported by two non-linear journal bearings was simulated as the base to an adjusted process. A unbalance mass was used as the excitation force (Table 1); the rotor is in stationary condition at 150 rad/s, the bearings clearance is of 180 μm, the central mass weight is of 2.1 kg, total length is of 690 mm and the diameter is of 12 mm.

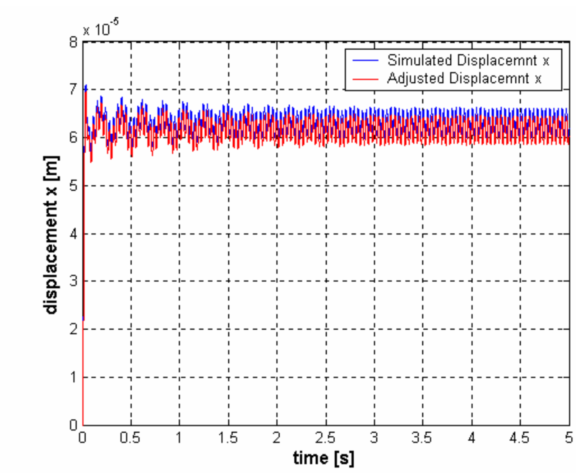
Table 1 shows the original parameters and adjusted parameters for this test. Fig. 16 represents the simulated and adjusted orbits of both bearings and the central mass. The total number of generations for this test was 20 generations and the population size was 60 individuals.

In order to simulate real displacements, a random noise is add to the simulate curves. This noise can reach until 10% of the signal.

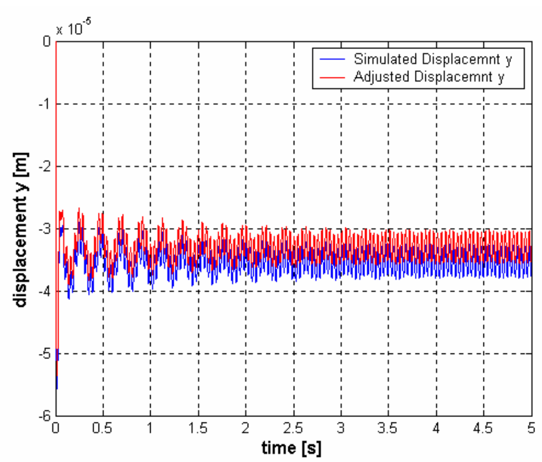
The adjusted parameter values (viscosity and unbalancing moment) are very close to the input values. The displacements, forces and orbits in Figs.17 up to 20 are also close to the generated signals. However, these results can be improved with more generations and population size in the GA method. These results show that GA can be use to adjust the proposed model.

Table 1 – Simulated parameters.

	Simulated Signal	Adjusted Signal
Viscosity in bearing 1 [Ns/m²]	0.06	0.064
Viscosity in bearing 2 [Ns/m²]	0.06	0.064
Unbalancing moment [kg.m]	0.0005	0.0005133

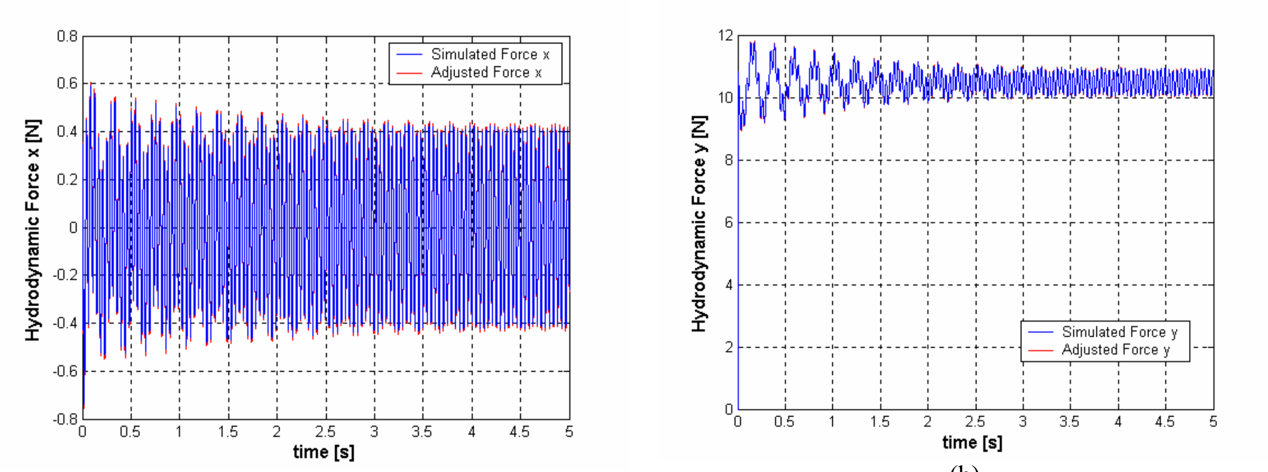


(a)



(b)

Figure 17 – Simulated and adjusted displacements of bearing 1: (a) x axes; (b) y axes.



(a) (b)

Figure 18 – Simulated and adjusted hydrodynamics forces: (a) x axes; (b) y axes.

The Fig. 18 shows that the simulated and adjusted forces are close. So, the little difference between the displacements in Fig. 17 is caused by the unbalance model and it is necessary to direct more resources to fitting this parameter, because it has a higher influence in the displacement.

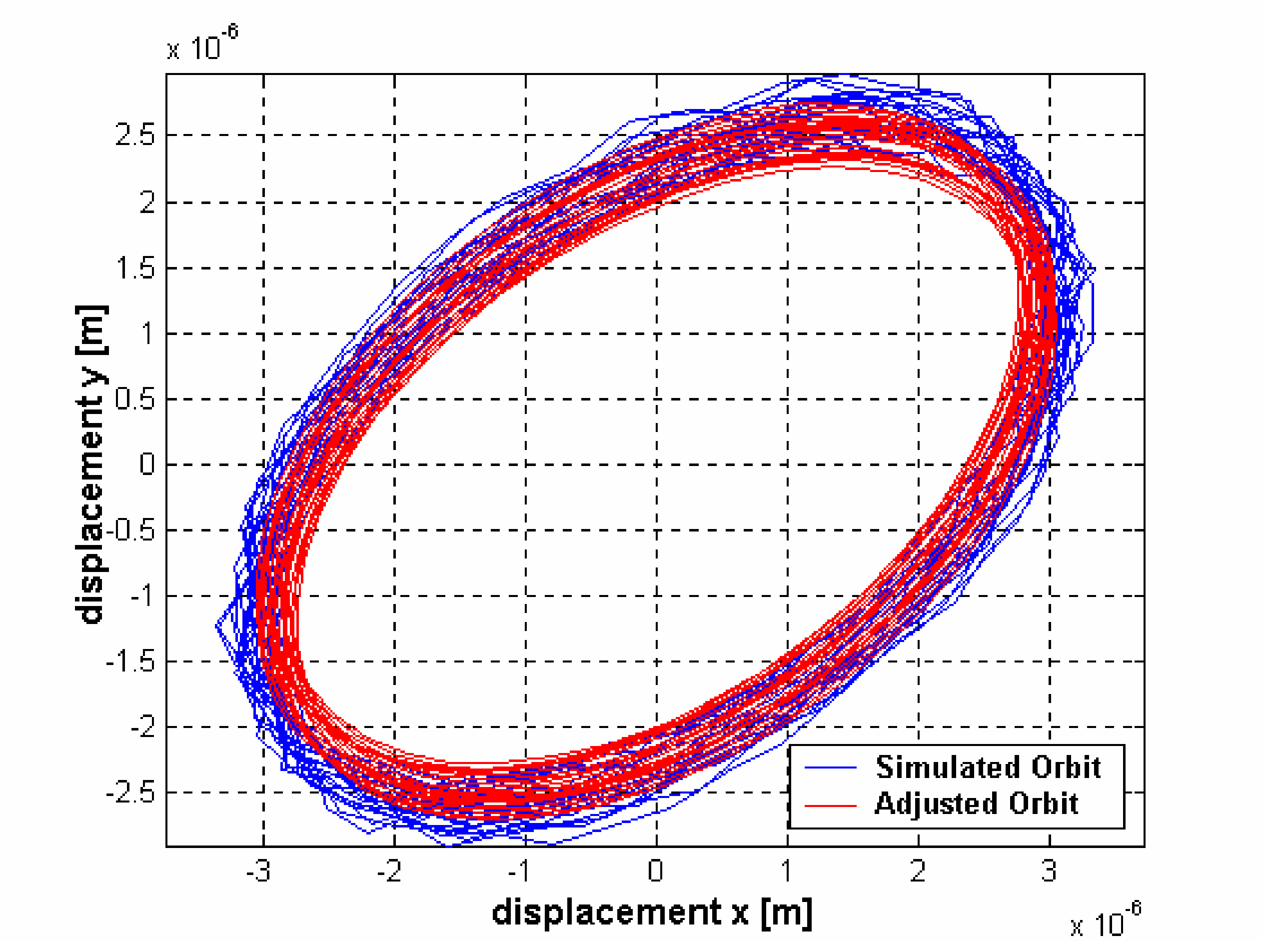


Figure 19 – Simulated and adjusted orbits of bearing 1.

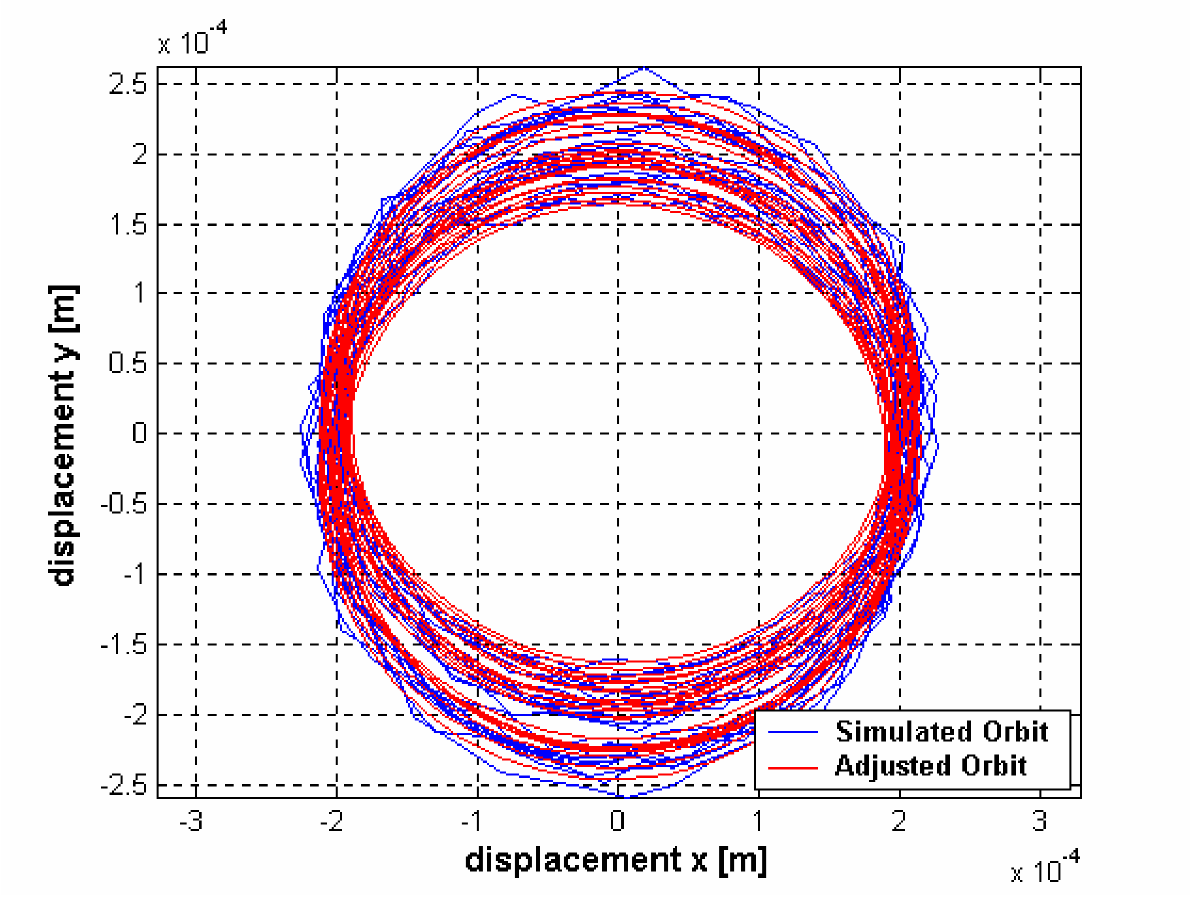


Figure 20 – Simulated and adjusted orbits: mass.

9. Conclusions

This work uses a non-linear journal bearing model in a Laval rotor. A time integrated solution gives the orbits of the bearings and mass, as well as hydrodynamic forces, excited by unbalance forces. The model is simulated, in order to verify the influence of some parameters in the system dynamic behavior. Some of these parameters, as viscosity of the oil in the bearing and unbalance moment, can be unknown in some experimental set up. So a fitting method, based in genetic algorithm, is proposed to adjust the orbits of the system in the bearings and in the disc. As more than one orbit is adjusted, the optimization process can be considered as a multi-objective one. With the aim of reduce the number of objectives functions a weight of each function is determined, joining to one single objective function. In this work these weights were considered the same. For future works, it is intended to determined different weights.

The simulation tests show that the proposed bearing forces model behaves as the well-known bearing models and close to real journals bearing. A comparison between these methods and linear methods are intended to the future.

The simulated fitting results show that the proposed adjusted method (Genetic Algorithm) can lead to satisfactory results. Otherwise, correct genetic algorithm parameters must be chosen to get this good result.

The objective function takes into account only the displacements at bearings and concentrated mass, once these parameters are easier to control in real cases. Otherwise, a sensitivity analysis could be very interesting to the weighted displacements, in x and y directions, in the objective function.

Experimental tests are going to be accomplished in order to adjust the model to real results.

10. Acknoewledgements

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