JOURNAL BEARING ORBITS FITTING WITH HYBRID META-HEURISTIC METHOD

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Abstract. *A hybrid meta-heuristic method is proposed to adjust the parameters of a rotor-bearing model. In this way, a methodology is obtained, aiming at calibrating the parameters of the mathematical model of a rotating system, as compared to experimental data. This model is written by using the finite element method to represent the shaft and the disc of the flexible rotor. The journal bearings are modeled by using a nonlinear hydrodynamic force equation. The gyroscopic system is represented by a flexible shaft with a disc at its mid point, supported by two journal bearings. An unbalance excitation force is applied to the disc. The following parameters are to be adjusted: the unbalance moment and the absolute viscosity of each bearing. The hybrid fitting method is formed by a Genetic Algorithm code followed by a Simulated Annealing program. The first one is used to obtain a first estimate of the parameters with respect to their real values. The Simulated Annealing is used to refine the solution. In order to simulate an experimental orbit, noise is added to the numerical simulated orbit. This simulated orbit is considered in this work as a reference for the updating procedure. Experimental data will be used in future work, but the present contribution intends to test and validate the fitting strategy. An objective function is formulated by taking into account the position of the center of the shaft in the bearing (locus) and the elliptical parameters of the orbit. In building the objective function, a weight is associated to each parameter, denoting the relative importance of each one in the fitting process. The Genetic Algorithm and the Simulated Annealing are tested to adjust the orbits, separately and together (forming a hybrid technique). The results obtained from both cases are compared.*
Keywords*: Journal Bearing, Updating Method, Genetic Algorithm, Simulated Annealing, Rotordynamic*

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 load capacity. 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, 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. Arruda and Duarte (1993) and Assis and Steffen (2003) also proposed updating methods in rotordynamic.

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.

Castro and Cavalca (2005) used genetic algorithm to estimate rotor-bearing system parameter through the fitting of orbits obtained by a non-linear model. Castro et. al. (2004) adjusted simulated bearing model orbits to experimental one, using genetic algorithm to determined the bearing and rotor unknown parameters.

In this work a multi-parameter method is used to update the model. Three metaheuristic models are considered and compared. The first 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 second procedure is based on Simulated Annealing, which is a search method that simulates the annealing thermal process. Finally, the third procedure is a mixed of both and uses a genetic algorithm to make an initial approximation and the simulated annealing to refine the final result. Some metaheursitic methods, as genetic algorithm and simulated annealing, were 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.

$$\frac{\partial}{\partial u}\left(h^3.\frac{\partial p}{\partial u}\right)+k^2.\frac{\partial}{\partial z}\left(\frac{h^3}{m}.\frac{\partial p}{\partial z}\right)=\frac{\partial h}{\partial u}+2.\frac{dh}{dt} \tag{1}$$

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:

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

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

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

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

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

$$G(x,y,a)=\int_a^{a+p}\frac{du}{(1-x.\cos(u)-y.sen(u))}=\frac{p}{\sqrt{1-x^2-y^2}}-\frac{2}{\sqrt{1-x^2-y^2}}.arctg\left(\frac{y.\cos(a)-x.\sin(a)}{\sqrt{1-x^2-y^2}}\right) \tag{5}$$

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

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

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

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

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 ($[C] = \alpha[M] + \beta[K]$). 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. Metaheristic Methods

3.1 Simulated Annealing

This algorithm explores the anology between the gradual cooling of a metal into a minimum energy crystaline structure and the search for a minimum in an optimization process.

The search for a minimum requires the definition of boundary constraints of the problem. It also requires a cost evaluation method of a particular solution, which can be used in all optimization problems. The algorithm carries out an iterative search for a better solution in the neighbourhood of the current solution. A new solution can become the starting point for a successive step trying to find better solutions, or even to avoid local minimum. This procedure must be carried on until reaches the stop criteria.

When there are no local solutions that improve the quality of the solution, the algorithm stops at the local solution. The local optimum trap makes the local search a heuristic restriction for many combinatory optimization problems. This is because it strongly depends on the initial point. A desirable property of any algorithm is its ability to obtain the global optimum independently of the starting point.

Another way of avoiding the local optimum trap is to start a search from other initial solutions, and then use the best solution as the solution to the algorithm. It is noted that the repetitive local searches converge asymptotically to the optimum solution using all solutions as starting points. However, this is neither feasible nor desirable when dealing with huge problems because they require considerable computational time.

The paradigm of the Simulated Annealing offers us an escape from the local optimum by analyzing the boundary of the current solution, and by accepting solutions that worsen the current solution with a certain probability. This is aimed at finding a better way to obtain the global optimum. (See Fig. 1).

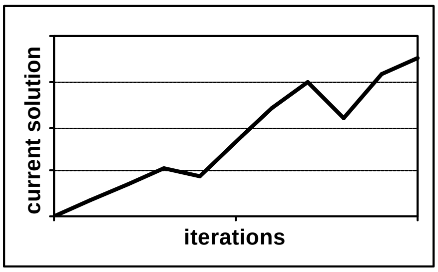


Figure 1 – Evolution of Objective Function using Simulated Annealing.

Annealing is a thermal process of melting a solid by heating and gradually cooling it. In the liquid phase, the molecules are scattered randomly, allowing them to reach the lowest possible level of energy – the stable state.

The physical process of annealing can be modeled successfully using simulation methods of condensed matter physics. Starting with the maximum temperature value, the cooling process can be described as follows:

For each temperature, the solid reaches thermal equilibrium characterized by the possibility of being in state *i* with energy E_i at temperature *T*. This condition is given by the Boltzmann distribution:

$$P_r\{\mathrm{E}=E_i\} = \frac{1}{Z(T)}\exp\left(\frac{-E_i}{k_B.T}\right) \tag{9}$$

Where $Z(T)$ is the partition function that depends on the temperature T and on the Boltzmann constant k_B.

$$Z(T) = \sum_j \exp\left(\frac{-E_j}{k_B T}\right) \tag{10}$$

As the temperature drops, the Boltzmann distribution is concentrated in the low energy state. And finally, as the temperature approaches zero, only the low energy state may occur.

Metropolis et al. (1953) presented a simple algorithm to simulate the evolution of a solid from its liquid state to its thermal equilibrium. This algorithm is based on Monte Carlo's technique, and it is described below.

If there is a random perturbation in a given solid state characterized by the position of its particles, and if the energy difference (ΔE) between the current state and the pertubated state is negative, it means that the perturbation results in a low energy state. But if $\Delta E \geq 0$, then the acceptance probability of this new state is given by:

$$P = \exp(\frac{-\Delta E}{k_B . T}) \tag{11}$$

A number r randomly chosen, in the interval [0, 1] is generated. And if $r < P(\Delta E)$, the new configuration is accepted, otherwise the last configuration to be accepted is used as a starting point in the search for a solution in the neighborhood. The acceptance rule described above is known as Metropolis' criterion, and the algorithm used is known as Metropolis' Algorithm.

By this criterion, the system attains thermal equilibrium. After a number of perturbations, using the criterion above, the probability distribution equals the Boltzmann distribution. (See Eq. (9))

Metropolis' Algorithm can be used to generate configuration sequences in a combinatory problem of optimization. In that case, the configuration plays the role of a solid state, while the objective function and the parameters that are searched become the energy and temperature respectively. The Simulated Annealing is seen as a sequence of Metropolis' Algorithm that uses a decreasing sequence of the control parameter.

The temperature (a control parameter) is slowly cooled after a number of searches in the neighborhood of the current state.

For this reason, some analogies are drawn between a particle physics system and a combinatory optimization problem.

- The solutions in an optimization problem are equivalent to states in a physical system.
- The cost of a solution is equivalent to the energy of a state.
- Choosing a solution in the neighborhood of an optimization problem is equivalent to the perturbation of a physical state.
- The global optimum of a combinatory problem is equivalent to the fundamental state of a system of particles.
- A local optimum of a combinatory problem is equivalent to a meta-stable structure in a system of particles.

With an iterative implementation, it is possible to obtain an algorithm for combinatory optimization problems. Figure 2 is a flow chart of the algorithm that shows its basics functions.

3.2 Genetic Algortihm

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. (12):

$$x_j = c_j + \sum_{i=0}^{k-1} b_i \cdot 2^i \cdot \frac{d_j - c_j}{2^k - 1} \tag{12}$$

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. 3 represents these two operators.

GA's are noted for robustness in searching complex spaces and they are best s uited 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 4 shows the genetic algorithm flowchart and its steps from the generation of initial population to the end of the search process.

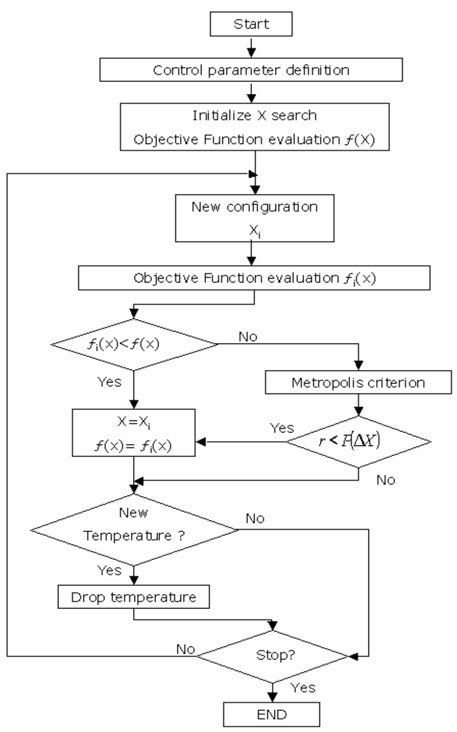


Figure 2 – Simulated Annealing Flowchart

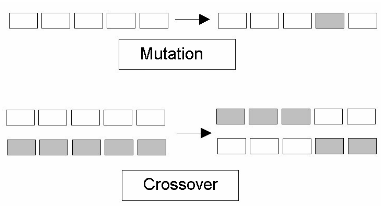


Figure 3 – Mutation and Crossover

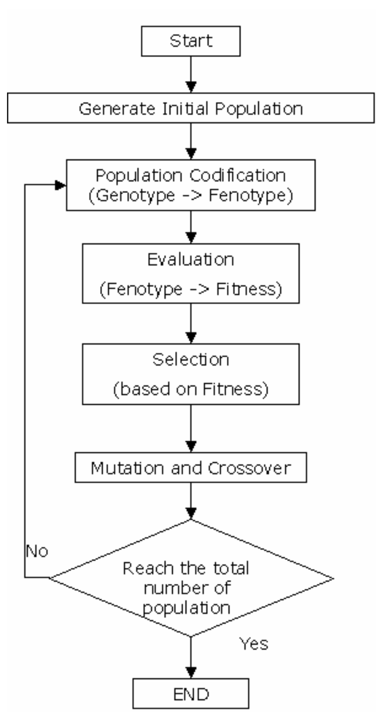


Figure 4 – Genetic Algorithm Flowchart

3.3 Hybrid Algorithm

Currently, the Simulated Annealing and the Genetic Algorithm are two stochastic methods largely used in different optimization problems. The hybrid method has generated promising results in many applications, mainly in highly complex problems.

While the SA uses the local movement to generate a new solution only by modifying the old one, the GA generates solutions by combining two different solutions. However, this does not necessarily make the algorithm better or worse than the others.

It is important to note that the GA and the SA are also bounded by the assumption that good solutions are probably found “near” the best know solutions, rather than chosen from a whole set of solutions. Otherwise they would not carry out a better search than that the random search.

The hybrid method was developed by arranging the algorithms in series. First the Genetic Algorithm was used, and then the Simulated Annealing. However, the algorithms parameters influences changes from each one separately, because in hybrid algorithm the genetic algorithm generates the first input to the simulated annealing. In this case, it is not necessary to reach the optimal GA solution. A sensitivity analysis of GA/SA parameters is carried out simultaneously, indicating the ideal parameters of both algorithms, defining the stop criteria of both algorithms.

Since the Genetic Algorithm has many solutions (population), it would be a good idea to use the method as a starting point for using the Simulated Annealing. Thus, the SA will have a pre-checked starting point in a universe of solutions.

4. Objective Function

In order to characterize an orbit got from the vibration of rotor system in the node of the bearing, a diagnostic technique (Bachschmid, Pennachi and Vania, 2004), which describes the elliptical form of the orbit, is taking into account. The analysis of the orbit is obtained by the degree of ellipticity and the inclination of the major axis of the orbit with respect to the horizontal axis as shown in Figure 5.

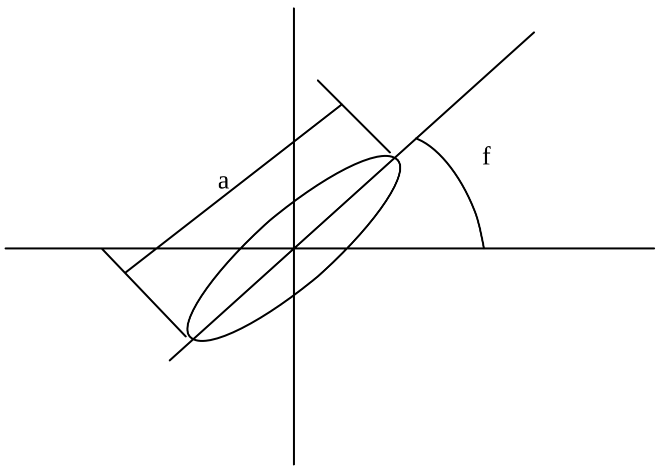


Figure 5 – Elliptical Orbit

Considering that the displacement in x direction is given by Equation 13 and the displacement in y direction by Equation 14.

$$x(t) = x_0 + x_c \cos(wt) + x_s \sin(wt) \quad (13)$$

$$y(t) = y_0 + y_c \cos(wt) + y_s \sin(wt) \quad (14)$$

Where x_0, x_s, x_c, y_0, y_s and y_c are Fourier coefficients.

So, the inclination of the major axis is:

$$j = 0.5 \tan^{-1}\left(\frac{2(x_c y_c + x_s y_s)}{x_c^2 + x_s^2 - y_c^2 - y_s^2} \right) \quad (15)$$

And the major radius is:

$$a = \sqrt{\frac{2(x_s y_c - x_c y_s)^2}{x_c^2 + x_s^2 + y_c^2 + y_s^2 - \sqrt{(y_c^2 + y_s^2 - x_c^2 - x_s^2) + 4(x_s y_s + x_c y_c)^2}}} \tag{16}$$

Finally, the degree of ellipticity can be given by the Shape and Directivity index (*SDI*), which is defined by:

$$-1 \leq SDI = \frac{|r^f| - |r^b|}{|r^f| + |r^b|} \leq 1 \tag{17}$$

Where r^f and r^b are respectively, the forward and harmonic components of the complex harmonic signal *p(t)* of frequency *?*.

$$p(t) = x(t) + jy(t) = r^f e^{jwt} + r^b e^{-jwt} \tag{18}$$

So, the difference between the simulated (or experimental) orbit and the adjusted one can be calculated by the difference of their parameters: degree of ellipticity (*SDI*), the major radius *a*, the inclination of the major axis *f* and the position of the center of the orbit referred to the center of the bearing (x_0, y_0) that is defined as locus. It can be done considering each parameters difference as an objective function. In order to solve this multi-objective optimization problem, a weight is adopted for each objective function that are summed to form only one objective function, which is represented by Eq. (19).

$$Ofunc = \sum_{orbit} \left(\begin{array}{c} w_j \left| \frac{j_{simulated} - j_{adjusted}}{j_{simulated}} \right| + w_a \left| \frac{a_{simulated} - a_{adjusted}}{a_{simulated}} \right| + w_{SDI} \left| \frac{SDI_{simulated} - SDI_{adjusted}}{SDI_{simulated}} \right| + \\ w_{locus} \left| x_0 \frac{x_{0simulated} - x_{0adjusted}}{SDI_{simulated}} \right| + w_{locus} \left| \frac{y_{0simulated} - y_{0adjusted}}{y_{0simulated}} \right| \end{array} \right) \tag{19}$$

5. Simulated Fitting

In order to simulate the response of a rotor system, the model represented by Fig. 6 was adopted. The model parameters are shown in Tab. 1.

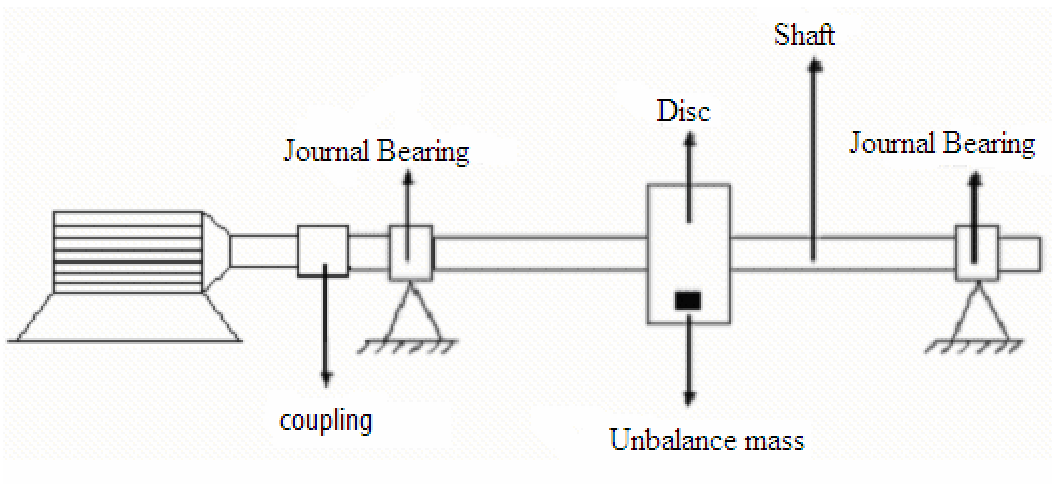


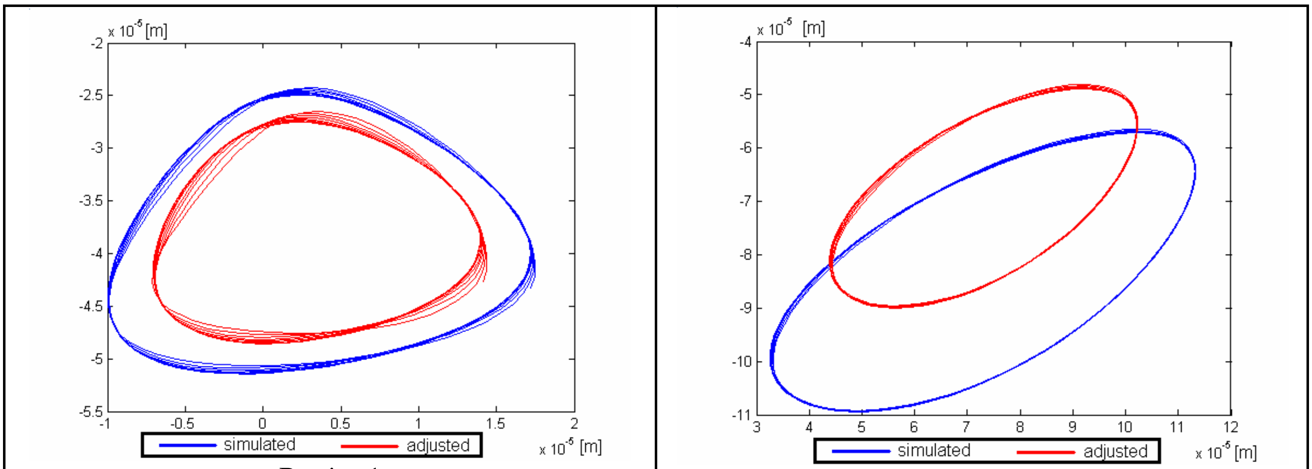
Figure 6 – Simulated model

Table 1 - Model parameters

Young's Modulus of the shaft	2.067×10^{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	20 mPa.s
Bearing clearance	180 µm
Unbalance Moment	5×10^{-4} kg.m
Stiffness coefficient in x and y direction for the coupling	46095×10^{3} N/m
Cross Stiffness coefficient for the coupling	2207610 N/m
Damping coefficient in x and y direction for the coupling	10949 N.s/m
Cross Damping coefficient for the coupling	-64322×10^{-5} N.s/m

The simulated orbits are obtained though these parameters and the oil viscosity and the unbalance moment are optimized variables. So, the adjusted process should approximate the value of the oil viscosity and the unbalance moment to the values shown in Tab. 1.

Figure 7 show the adjusted (red) orbit compared to the simulated one (blue) for Genetic Algorithm fitting process. Figure 8 represents the results of Simulated Annealing fitting process and Fig. 9 the results of Hybrid fitting process.



Bearing 1 Bearing 2

Figure 7 – Genetic Algorithm adjusted orbit

The number of generations considered in Genetic Algorithm fitting process was 40 and the population number was 50. So, the number of objective function evaluations was 2000. In Simulated Annealing process, the number of searching in the neighborhood was 25 and the number of change in temperature was 80. In that case, the number of evaluation of the objective function was also 2000. The parameters of the hybrid algorithm were 20 for the number of generations, 50 for the number of population, 20 for the number of searching in the neighborhood and 50 for the number of change in the temperature, totalizing 2000 of evaluation on objective function. As the number of evaluation is the same in all fitting process, it is possible to compare. In some cases, the final result is not good, because more evaluations are necessary.

The oil viscosity has an important influence on the locus of the shaft and the unbalance moment influences mainly the orbit amplitude. It was considered a weight of 0.3 for the locus and 0.2 for the other objective functions parameter (Eq. 19). So, the adjust of the oil viscosity has more importance than the adjust of unbalance moment. Table 2 show adjusted parameters for each fitting process.

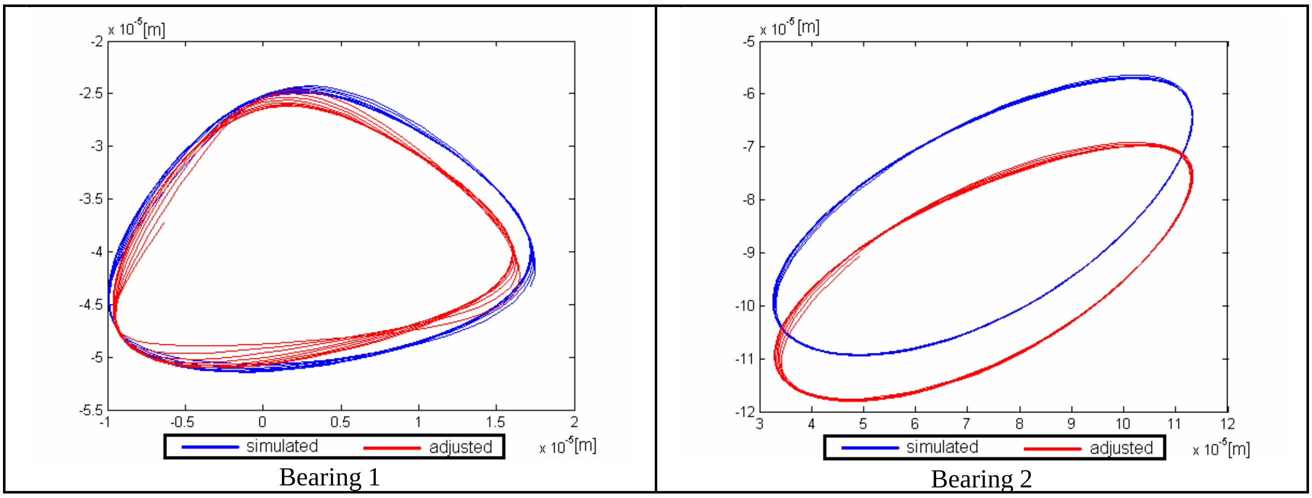


Figure 8 – Simulated Annealing adjusted orbit

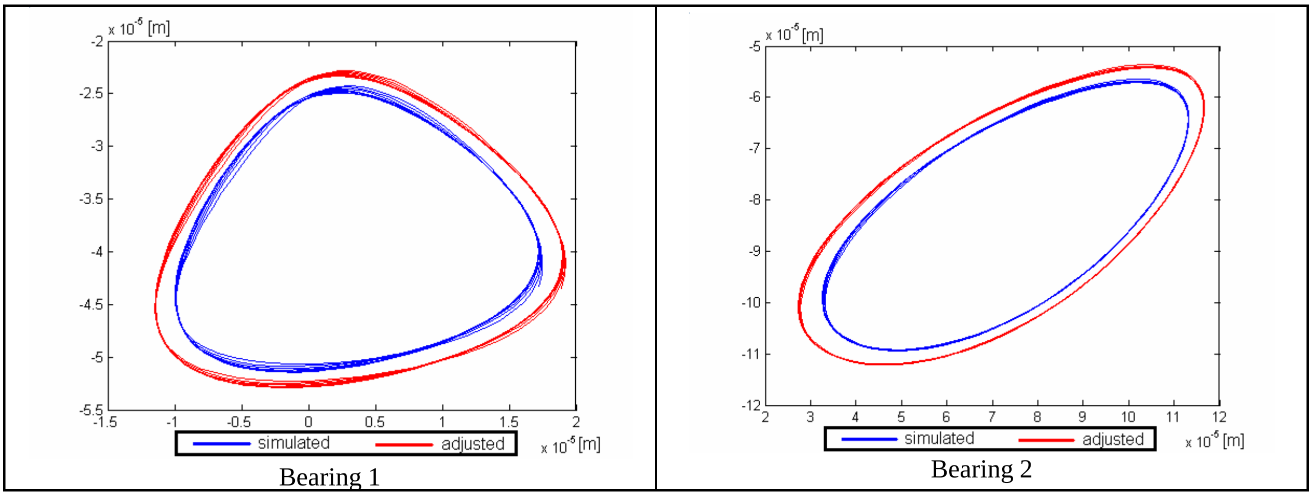


Figure 9 – Hybrid Algorithm adjusted orbit

Table 2 – Adjusted Parameter

Fitting process	Genetic Algorithm	Simulated Annealing	Hybrid Method	Expected Result
Unbalance Moment (kg.m)	4.10^{-4}	$-4.602286.10^{-4}$	$5.593458.10^{-4}$	5.10^{-4}
Oil viscosity in bearing 1 (mPa.s)	15.71	9.9	22.92	20
Oil viscosity in bearing 2 (mPa.s)	30	15.05	19.57	20

With the number of evaluations (2000) considered to fit the orbits, the hybrid method could reach good results. The other methods need more evaluations. The optimization parameters as number of generations, population size, probability of crossover and mutation, number of searching in neighborhood, number of change in temperature Boltzmann constante and decrease factor of temperature are very important to the convergence of the three methods. And a sensitivity analysis of GA/SA parameters is carried out to verify the ideal values of parameters for the fitting process.

6. Conclusions

This work uses a non-linear journal bearing model in a rotor system modeled by a Finite Element Model. A time integrated solution gives the orbits of the bearings 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 the three fitting methods, based in genetic algorithm and simulated annealing, are proposed to adjust the orbits of the system in the bearings. 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.

The simulated fitting results show that the proposed adjusted methods can lead to satisfactory results. Otherwise, correct genetic algorithm and simulated annealing parameters must be chosen to get this good result. So, a sensitivity analysis on these parameters is necessary to determine the ideal values for a fitting process. The hybrid algorithm presents better results than others, because the GA is used to make an approximation and the SA is used to refine the final result.

The objective function takes into account only the displacements at bearings, 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.

7. Acknoewledgements

The authors would like to thank CNPq, FAPESP and CAPES for the financial support for this work.

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