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Model Based Diagnosis of Malfunction in Rotor Systems using Genetic Algorithms and Equivalent Loads Method

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Abstract: A model based method for diagnosis of malfunction in rotor systems using equivalent loads and genetic algorithm method is presented. The presence of the fault changes the dynamic behavior of the system, and this change is taken into account by equivalent loads acting on the undamaged system model. Equivalent loads are fictitious forces and moments acting in the model of the undamaged system, which generates a dynamic behavior identical to that of the real damaged system. The mathematical representation of the equivalent loads is referred to as fault model. The identification of the fault is treated as an inverse problem, where the parameters of the fault are formulated as an optimization problem through the method of the equivalent loads, and the method of the genetic algorithms is implemented to search for the best estimate of these fault parameters. Genetic algorithms are stochastic search algorithms based on the mechanics of nature selection and natural genetics, which is designed to efficiently search large, non-linear, discrete and poorly-understood search space, where expert knowledge is scarse or difficult to model and where classical optimization techniques are limited in solving most of the inverse problems found in dynamic systems. A typical fault due to the unbalance was considered in this work. Numerical simulations and experimental results were accomplished for different rotations and measurement configurations. The results indicate that the method behaved very well in the identification of the fault for unbalance, demonstrating your potentiality for application the other types of faults.

Keywords: fault identification, rotating machinery, genetic algorithms

NOMENCLATURE

E = Yong's modulus of the shaft, Pa
rot = rotor speed, Hz
u = product of unbalance mass and eccentricity, Kg.m
XYZ = fixed reference frame

Greek Symbols

ρ = shaft density, Kg/m^3
ϕ,ψ = angular generalized displacements
η,ξ = rotating reference frame

Subscripts

comp relative to computed
exp relative to experimental
simu relative to simulated
n relative to the node number
o relative to the undamaged system

INTRODUCTION

In rotating machinery, commonly used in mechanical systems, including machining tools, industrial turbo-machinery, aircraft gas turbine engines, etc; it is inevitable that malfunctions occur during operation which may damage or totally destroy the system if not detected previously. Therefore, it is advantageous to early detect developing faults and to perform explicit identification of fault parameters before the machine will crash or stop. Diagnosing on-line the health condition of rotating machinery reduces maintenance costs and prevents the rotor system to break down. However, how to locate and configure a malfunction in rotating machine is just an inverse problem and not easy to tackle.

Different model based identification methods for finding malfunctions in rotor systems from measured vibration signals have been developed. These methods work either time or frequency domain depending on the malfunction type and the operating state for which the vibration data are available.

Vibration based identification of malfunctions, such as rotor unbalance, rotor bends, cracks, rubs, misalignment and fluid induced instability, based on the qualitative understanding of measured data, is well developed and widely used in practice (Santiago, 2004; Pederiva, 1992). However, the quantitative part, i.e. the estimation of the extent of faults and their locations in rotating machinery, has been an active area of research for many years (Sinha et al., 2004).

In this context, Markert et al. (2001) proposed a model based method for on-line identification of malfunctions in rotor systems based on the idea that faults can be represented by equivalent loads acting on the linear model of the undamaged system. To identify the fault parameters, the difference of the theoretical equivalent loads and the equivalent loads from measured data is minimized by a least squares. Bachschmid et al. (2002) proposed a method for identification based in model for multiple faults, where the identification is made by the least squares in the frequency domain. Sekhar (2003) proposed a model based technique for identification of a crack, combining an approach based on model through equivalent loads and an approach using the wavelet technique. Furtado et al. (2005) presented some results about diagnostic and identification of faults in a rotor system using artificial neural network and model based methods. Tiwari and Chakravarthy (2006) presented an identification algorithm for simultaneous estimation of residual unbalances and bearing dynamic parameters by using impulse response measurements for multi-degree-of-freedom flexible rotor–bearing systems. Pennacchi et al. (2006) proposed a technique of fault identification using the least squares in the frequency domain that proved to be quite robust in the unbalance identification even if the submodels of rotating machine are not fine-tuned.

In the literature, most of the optimization algorithms used in the methods of faults identification in rotor systems is based in numeric methods of classic optimization, i.e. methods based on the gradient calculation (e.g. least squares method). However, in the last years, search methods based on biological and physical phenomena have been developed and applied in the optimization of engineering systems, as for example, neural networks and evolutionary computation. The evolutionary computation is based on an adaptive process of optimization where the genetic algorithm (GA) is the most popular.

The genetic algorithms were used in this work due to its flexibility, relative simplicity of implementation, efficiency in accomplishing global search in adverse environments, besides its robustness in solving inverse problems in engineering. However, most of the works related to rotor systems found in the literature use the GA either for the optimal design of rotor-bearing systems or for the design optimization of journal bearing. For example, Choi and Yang (2000) proposed a GA for an optimal dynamic design of a rotor-bearing system with the objective of minimizing the total weight of the shaft to yield the critical speeds as far from the operating speed as possible. Assis and Steffen Jr (2002) presented a methodology based on genetic algorithm to identify unknown bearing parameters of flexible rotors. Saruhan et al. (2004) focused the use of GAs in developing an efficient optimum design method for tilting-pad bearings. Castro and Cavalca (2006) proposed the use of non-linear model updating applying a meta-heuristic search method, the genetic algorithm, in order to obtain a methodology which allows the fitting of parameters of mathematical models of rotating systems. Saldarriaga et al. (2006) presented an optimization-based balancing technique in which trial weights are not necessary. The proposed balancing method is based on pseudo-random optimization techniques using genetic algorithms. The basic idea is to obtain the flexible rotor unbalance response, which is obtained by Finite Element (FE) model in which the unbalance masses and their corresponding angular positions are the design variables.

In the context of fault identification using GA, Marano and Pederiva (2006) presented a model based method for identification of faults in rotor systems, where the identification of the fault was treated as an inverse problem. So, the parameters of the fault were formulated as an optimization problem through the method of equivalent loads, and the method of genetic algorithms was implemented to search the best estimate of the fault parameters. A typical fault due to the unbalance was considered and numeric simulations were accomplished for different rotations and measurement configurations. The obtained numeric results showed that the method behaved very well in the fault identification for unbalance, demonstrating its potentiality for practical applications.

In this work, the idea was to use the methodology of fault identification based on genetic algorithms and equivalent loads proposed by Marano and Pederiva (2006) for diagnosis of unbalance in a real rotor system, in order to validate the proposed methodology through experimental results. Moreover, few works found in literature about this theme presented experimental results.

EQUIVALENT LOADS METHOD

The model based method presented for identification of malfunctions is based on the idea that faults can be represented by virtual loads acting on the linear model of the undamaged system.

Equivalent loads are fictitious forces and moments which generate the same dynamic behavior as the real non-linear damaged system does. So, system models being originally linear remain linear and unchanged, even if non-linear faults occur.

The method avoids non-linearities, which are normally brought into the system equations by fault models, representing the fault-induced change in the dynamic behavior of the system in terms of equivalent loads. Therefore, to handle the system equations, only simple and fast mathematical procedures are necessary, and the identification of the nature, position and severity of faults can be carried out on-line during operation, even if the number of degrees of freedom is very high (Markert et al., 2001).

Mathematical Description

The vibrations $\mathbf{q_o}(t)$ at N degrees of freedom of the undamaged rotor system due to the load $\mathbf{F_o}(t)$ during normal operation (e.g. residual unbalance, weight) are described by linear equations of motion:

$$\mathbf{M_o}\,\ddot{\mathbf{q}}_\mathbf{o}(t) + (\Omega\mathbf{G_o} + \mathbf{C_o})\,\dot{\mathbf{q}}_\mathbf{o}(t) + \mathbf{K_o}\,\mathbf{q_o}(t) = \mathbf{F_o}(t) \tag{1}$$

where $\mathbf{M_o}$, $\mathbf{G_o}$, $\mathbf{C_o}$ and $\mathbf{K_o}$ are the mass, gyroscopic, damping and stiffness matrix of the undamaged system, respectively.

The fault induced system change depends on the malfunction type and the malfunction parameters contained in the vector β, which describes the fault parameters: type, magnitude and location of the fault. So, one can imagine that the fault induced change in the vibrational behavior could also be caused by additional loads $\Delta\mathbf{F}(\beta,t)$ acting on the undamaged system:

$$\mathbf{M_o}\,\ddot{\mathbf{q}}_\mathbf{o}(t) + (\Omega\mathbf{G_o} + \mathbf{C_o})\,\dot{\mathbf{q}}_\mathbf{o}(t) + \mathbf{K_o}\,\mathbf{q_o}(t) = \mathbf{F_o}(t) + \Delta\mathbf{F}(\beta,t) \tag{2}$$

As the system matrices remain unchanged, the rotor model stays linear, and only the equivalent loads induce the change in the dynamic behavior of the undamaged linear rotor model (Bach and Markert, 1998).

Faults Models

For the proposed model based fault identification method each fault has to be represented by a mathematical model describing the relation between the fault parameters β and the equivalent force $\Delta\mathbf{F}(\beta,t)$. This way, the mathematical representation of equivalent loads is referred to *Fault Model*.

Fault models are being developed for prominent known faults like unbalance, transverse fatigue crack, rotor-stator rub, rotor bow, misalignment, etc. Other malfunctions of rotor systems and their representation in terms of equivalent loads are described in details in Platz et al. (2001).

In this work, for illustrating the relation between fault parameters and the corresponding equivalent load, a single unbalance u_n with the phase angle δ_n acting on the rotor at position number n was considered, according to Fig. 1.

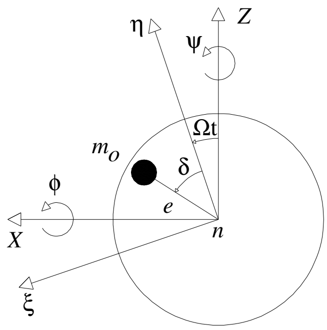

Figure 1 – Node *n* of the rotor disk with unbalance.

Defining the vector ζ_n of generalized displacements of the node n as

$$\zeta_n = [x_n \;\; \phi_n \;\; z_n \;\; \psi_n]^T \tag{3}$$

the forces due the unbalance acting in this node n are

$$\mathbf{F}_{x_n} = \mathrm{m_o}.\mathrm{e}.\Omega^2.\,\mathrm{sen}\,(\Omega t + \delta) = \mathrm{m_o}.\mathrm{e}.\dot{\theta}^2.\,\mathrm{sen}\,(\theta + \delta) \tag{4}$$

$$\mathbf{F}_{z_n} = \mathrm{m_o}.\mathrm{e}.\Omega^2.\,\cos\,(\Omega t + \delta) = \mathrm{m_o}.\mathrm{e}.\dot{\theta}^2.\,\cos\,(\theta + \delta) \tag{5}$$

or

$$\mathbf{F}_{x_n} = \mathrm{m_o}.\mathrm{e}.\cos\,(\delta).(\dot{\theta}^2.\,\mathrm{sen}\,\theta) + \mathrm{m_o}.\mathrm{e}.\mathrm{sen}\,(\delta).(\dot{\theta}^2.\,\cos\theta) \tag{6}$$

$$\mathbf{F}_{z_n} = \mathrm{m_o}.\mathrm{e}.\cos\,(\delta).(\dot{\theta}^2.\,\cos\theta) - \mathrm{m_o}.\mathrm{e}.\mathrm{sen}\,(\delta).(\dot{\theta}^2.\,\mathrm{sen}\,\theta) \tag{7}$$

Denominating as fault parameters due to unbalance, the parameters $\beta = [\mathrm{m_o},\ \mathrm{e},\ \delta\,]$, and rewriting the Eq. (6) and Eq.(7) in the matricial form, the equivalent forces acting in node n are

$$\Delta\mathbf{F}(\beta,t) = \begin{Bmatrix} \mathbf{F}_{x_n} \\ \mathbf{M}_{\phi_n} \\ \mathbf{F}_{z_n} \\ \mathbf{M}_{\psi_n} \end{Bmatrix} = \begin{bmatrix} (\mathrm{m_o}.\mathrm{e}.\cos(\delta)) & (\mathrm{m_o}.\mathrm{e}.\mathrm{sen}(\delta)) \\ 0 & 0 \\ -(\mathrm{m_o}.\mathrm{e}.\mathrm{sen}(\delta)) & (\mathrm{m_o}.\mathrm{e}.\cos(\delta)) \\ 0 & 0 \end{bmatrix} . \begin{Bmatrix} \dot{\theta}^2.\mathrm{sen}\,\theta \\ \dot{\theta}^2.\cos\theta \end{Bmatrix} \tag{8}$$

where the equivalent moments were considered negligible due to thickness of the disk.

Therefore, in this study, the excitation form (harmonic function) was considered known and the parameters to be identified were associated with input matrix of the rotor system. So, the problem of identification was then reduced to an identification procedure of forces with known parameters of the system, where the fault parameters were considered as design variables that will be identified through an optimization algorithm. Besides, due to the fact that the unbalance is at node *n*, the equivalent loads only act on node *n*, being null in all other nodes.

GENETIC ALGORITHMS METHOD

Optimization Algorithms

There are many kinds of optimization algorithms which can be classified into two groups: one is the classical gradient-based optimization method including quasi-Newton method, quadratic programming algorithm, etc; the other group is composed by the recently developed global searching optimization methods, including genetic algorithm, simulated annealing method, etc (Tao et al., 2001).

The major application of optimization procedures in mechanical systems is devoted to inverse problems, i.e., parameter estimation. The determination of unknown parameters in rotating machinery is a hard task, but the optimization algorithms represent an alternative and promising way for parameter identification.

In practical engineering, most inverse problems fall under three categories: reconstruction, identification and combination of the previous two. All of the problems of these three categories refer to the determination of missing process conditions or some other externally applied unknown inputs, it just means to seek the good, if not the best, solution to match the given outputs from input variable space.

The classical gradient-based methods are reasonably effective for well-behaved objective functions, because the gradient of the function helps to guide the direction of the search. However, it is well known that classical methods can fail in solving most inverse problems found in dynamic systems (Assis and Steffen Jr, 2002).

Genetic Algorithms: a review

Invented by Holland (1975), the genetic algorithm is a directed random search technique which can find the global optimal solution in complex multi-dimensional search spaces. A GA is modelled on natural evolution in that the operators employed are inspired by the natural evolution process. These operators, known as genetic operators, manipulate individuals in a population over several generations to improve their fitness gradually.

GAs do not use much knowledge about the problem to be optimized and do not deal directly with the parameters of the problem. They work with codes which represent the parameters. Thus, the first issue in a GA application is how to code the problem under study, i.e. how to represent the problem parameters. GAs operate with a population of possible solutions, not only one possible solution, and the second issue is therefore how to create the initial population of possible solutions. The third issue in a GA application is how to select or devise a suitable set of genetic operators (Phan and Karaboga, 2000).

The greater advantage of the genetic algorithm is that it undertakes a wider search in the entire design variable space than the classical gradient-based algorithms. This is mainly due to the random character of the procreation process in the genetic operators (Goldberg, 1994). Besides, the GAs do not need the use of derivatives, and unlike the techniques of classical optimization that cannot get out of the local optimum point when they reach a false peak, GAs can get out of the local optimum using the genetic algorithm operators (crossover and mutation) to find a global optimum (Choi and Yang, 2000). For that, it can be considered robust methods, because genetic algorithms are do not influenced by local optimum, noise in the search space and continuity lack.

The Algorithm 1 illustrates the process of GA, where it maintains a population of encoded solutions and guides the population towards the optimum solution. Thus, it searches the space of possible individuals and seeks for high-fitted strings (Tao et al., 2001).

Algorithm 1 – *Genetic algorithms*:

1. Create an initial population of fixed size (usually, randomly).
2. Evaluate all the individuals (apply some function or formula to the individual).
3. Select a new population from the old population based on the fitness of the individual as given by the evaluation function.
4. Apply some genetic operators (mutation and crossover) to members of the population to create new solutions.
5. Evaluate these newly created individuals.
6. Repeat steps 3-5 (one generation) until the termination criteria has been satisfied (usually perform for a certain fixed number of generations).

Genetic Operators

There are three common genetic operators: selection, crossover and mutation. Some of these operators were inspired by nature and, in the literature, many versions of theses operators can be found (Phan and Karaboga, 2000). The choice or design of operators depends on the problem and the representation scheme employed.

A brief description of the most important genetic operators is presented in the following.

Selection is the first genetic operator of GA used to create a new generation. This operator selects the fitter individuals of the former population to participate of process that will form a new population. The selection procedure has a significant influence on driving the search towards a promising convergence region and finding good solutions in a short time. In GAs there are mainly two selection procedures: proportional selection and ranking-based selection (Goldberg, 1994). This work uses a proportional selection called roulette wheel method.

Once the parents have been selected, the recombination operator or *crossover* operator is used. This operator is used to create two new individuals (children) from two existing individuals (parents) picked from the current population by the selection operation. In this work, to assure each substring corresponding to various parameters has equal chance for crossover, two-point crossover was implemented with a given probability by choosing two random points in the selected pair of strings and exchanging the substrings defined by the chosen points.

After the children have been created, each one is subject to the *mutation* operator. In this operator, all individuals in the population are checked bit by bit and the bit values are randomly reversed according to a specified rate, i.e. the role of this operator is to introduce new genetic materials (*genes*) to the chromosomes with a certain probability, preventing the inadvertent loss of useful genetic material in earlier phases of evolution (Goldberg, 1994). This way, the mutation operator forces the algorithm to search new areas, and eventually, it helps the GA avoid premature convergence and find the global optimal solution.

Control Parameters

Population size (number of individuals in the population), crossover rate and mutation rate are important control parameters of a simple GA. Several researchers have studied the effect of these parameters on the performance of GAs and the main conclusions found in the literature are as follows (Michalewicz, 1994).

A large population size means the simultaneous handling of many solutions and increases the computation time per iteration; however since many samples from the search space are used, the probability of convergence to a global optimal solution is higher than when using a small population size. In general, the population size affects both the ultimate performance and the efficiency of GAs.

The crossover rate (P_c) determines the frequency of the crossover operation, i.e. it controls the rate at which solutions are subjected to crossover. A low crossover rate decreases the speed of convergence for a promising convergence region. And, if the rate is too high, it leads to saturation around one solution (Zimmerman and Yap, 1999). Typical values of P_c are in the range of 0.5-1.0.

The mutation operation is controlled by the mutation rate (P_m). Large values of P_m will transform the GAs into a purely random search algorithm, i.e. a high mutation rate introduces high diversity in the population and might cause instability. However, too small values will cause the premature convergence of GAs to suboptimal solutions (Mitchell, 1996). Typically, P_m is chosen in the range of 0.005-0.1.

FAULT IDENTIFICATION METHOD

Mathematical Model

During the last 30 years, theoretical models have been playing an increasing role in the rapid resolution of problems in rotating machinery. Among several applications, these models are necessary in methods of fault detection in machines with base in the known theoretical behavior.

In this work, a mathematical model was obtained by Finite Element Method (FEM), according to Lalanne and Ferraris (1998).

Design Variables

The faults considered are additional unbalance in the disk 1 (Case 1) and in the disk 2 (Case 2), where the fault parameters formulated as an optimization problem through the method of the equivalent loads are: additional unbalance mass (m_o), eccentricity (e) and the phase angle (δ). In other words, $\beta = [m_o, e, \delta]$.

This way, the fault parameters are identified in an optimization process using the method of the genetic algorithms, in order to obtain the best results for the parameters searching.

Objective Function

The GA works with an objective function that is a quantity to be minimized by exploring a search space. This function correlates, in the time domain, the experimental (or simulated) displacements with the computed displacements obtained from the FEM model.

In this work, the function adopted was a multi-objective function given by:

$$\Lambda = w_1 \cdot \sum_{i=1}^{npto} (x_{comp} - x_{simu/exp})^2 + w_2 \cdot \sum_{i=1}^{npto} (z_{comp} - z_{simu/exp})^2 , \qquad \sum_{i=1}^{2} w_i = 1 \tag{9}$$

where the variable w is the weight adopted for each objective function that is summed to form only one objective function.

NUMERICAL SIMULATIONS

In order to investigate the feasibility and utility of the proposed method, numerical simulations were accomplished using the rotor model shown in Fig. 2. This rotor model consists of a flexible shaft with two rigid disks and two bearings, discretized by seven nodes.

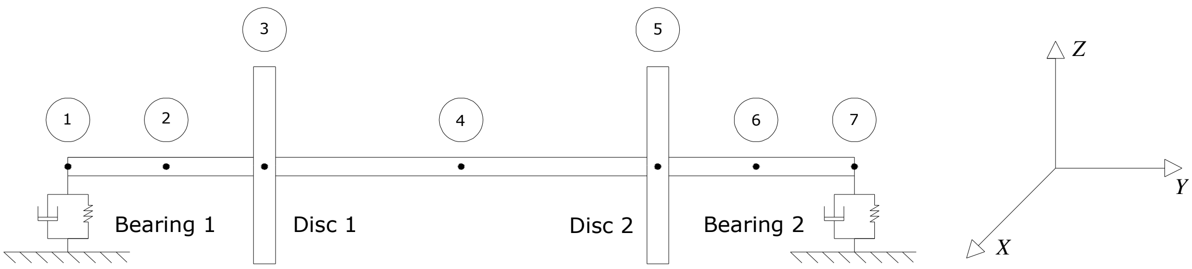

Figure 2 – FEM rotor model.

The real parameters of the rotor-bearing system are listed in Tab. 1.

Table 1 – The real parameters of rotor-bearing system.

Bearing 1 and 2				Disk 1 and 2		Shaft	
K_{xx} (N/m)	K_{zz} (N/m)	C_{xx} (Ns/m)	C_{zz} (Ns/m)	M (Kg)	D (m)	D (m)	L (m)
5e+6	1e+7	2	2	4	18e-2	17e-3	720e-3

To simulate a possible fault, an unbalance mass was added to disk 2, i.e. a possible fault by additional unbalance. The numerical simulations were accomplished for two rotations: below the first critical speed (40 Hz) and between the first and the second critical speed of the model (70 Hz).

Moreover, different measurement configurations were simulated in the horizontal and vertical direction, and, in order to simulate more realistic results, an additive random noise of 10% was added.

In this work, the parameters to be optimized were represented in a string form, and a binary string representation method was used. When a binary representation scheme is employed, an important issue is to decide the number of bits used to encode the parameters to be optimized.

This way, the size of binary string in the implemented algorithm is equal to the product of the numbers of variables and the number of the bit of each variable. As the number of design variables is equal to three and the number of the bit of each variable was chosen equal to eight, hence the size of the string is twenty-four.

So, the genetic parameters were determined as following: *Pop_size* = 96 (initial population size), P_c = 0.85 (crossover rate), P_m = 0.01 (mutation rate), *Max_gen* = 150 (number of generations).

Tables 2 to 6 show the real values and the identified values of the searched parameters for different configurations. The interval of time of these simulations was of 10 seconds, being used 10240 sampling points (*npto*).

Table 2 – Obtained results measuring in the nodes 2, 4 and 6 (Shaft Elements) in the horizontal and vertical direction.

Design Variables (Real values)		Identified Values *(error)* *rot = 40 Hz*	Identified Values *(error)* *rot = 70 Hz*
m_o = 6.0 e-04	(Kg)	6.2161e-04 (+ *3.60 %*)	6.0224e-04 (+ *0.37 %*)
e = 8.0 e-02	(m)	7.7255e-02 (- *3.43 %*)	7.9607e-02 (- *0.49 %*)
δ = 7.8540e-01	(rad)	7.8847e-01 (+ *0.39 %*)	7.8847e-01 (+ *0.39 %*)

Table 3 – Obtained results measuring in the nodes 2 and 6 (Shaft Elements) in the horizontal and vertical direction.

Design Variables (Real values)		Identified Values (*error*) *rot = 40 Hz*	Identified Values (*error*) *rot = 70 Hz*
m_o = 6.0 e-04	(Kg)	6.3571e-04 (+ *5.95 %*)	6.2987e-04 (+ *4.97 %*)
e = 8.0 e-02	(m)	7.5686e-02 (- *5.39 %*)	7.6078e-02 (- *4.90 %*)
δ = 7.8540e-01	(rad)	7.7615e-01 (+ *1.17 %*)	7.8847e-01 (+ *0.39 %*)

Table 4 – Obtained results measuring in the node 4 (Shaft Element) in the horizontal and vertical direction.

Design Variables (Real values)		Identified Values (*error*) *rot = 40 Hz*	Identified Values (*error*) *rot = 70 Hz*
m_o = 6.0 e-04	(Kg)	6.2821e-04 *(+ 4.70 %)*	6.2243e-04 *(+ 3.73 %)*
e = 8.0 e-02	(m)	7.6470e-02 *(- 4.41 %)*	7.7255e-02 *(- 3.43 %)*
δ = 7.8540e-01	(rad)	7.7615e-01 *(- 1.17 %)*	7.8847e-01 *(+ 0.39 %)*

Table 5 – Obtained results measuring in the Bearings 1 and 2 in the horizontal and vertical direction.

Design Variables (Real values)		Identified Values *(error)* *rot = 40 Hz*	Identified Values *(error)* *rot = 70 Hz*
m_o = 6.0 e-04	(Kg)	6.2738e-04 *(+ 4.56 %)*	6.2738e-04 *(+ 4.56 %)*
e = 8.0 e-02	(m)	7.6471e-02 *(- 4.41 %)*	7.6470e-02 *(- 4.41 %)*
δ = 7.8540e-01	(rad)	7.7616e-01 *(- 1.17 %)*	7.7615e-01 *(- 1.17 %)*

Table 6 – Obtained results measuring in the Disks 1 and 2 in the horizontal and vertical direction.

Design Variables (Real values)		Identified Values *(error)* *rot = 40 Hz*	Identified Values *(error)* *rot = 70 Hz*
m_o = 6.0 e-04	(Kg)	5.9907e-04 *(- 0.15 %)*	5.6752e-04 *(- 5.41 %)*
e = 8.0 e-02	(m)	8.0000e-02 *(0.00 %)*	8.4706e-02 *(+ 5.88 %)*
δ = 7.8540e-01	(rad)	7.8847e-01 *(+ 0.39 %)*	7.8847e-01 *(+ 0.39 %)*

Analyzing the obtained results of the simulations, it is noticed that even with noise in the measurements, different rotation values and different measurement configurations, the identification method presented satisfactory results. Moreover, it is worth to point out that this identification used values of the residual unbalance previously identified.

EXPERIMENTAL VALIDATION

Experimental set-up

The experimental set up (Fig. 3) consists of a 3 CV electric motor (frequency range of 1 to 60 Hz), a coupling, two identical disks, a flexible shaft and two ball bearings. The dimensions and characteristics of these elements are: shaft length = 0.720 m, shaft diameter = 0.0170 m, diameter of the disks = 0.1800 m, thickness of the disks = 0.020 m, distance between the disks = 0.0360 m, distance between the disks and the bearings = 0.180 m. The material for shaft and disks is steel ($E = 2.11\times10^{11}$ Pa, $\rho = 7800$ kg/m^3). The stiffness coefficients and damping coefficients of the coupling are: $K_{xx} = K_{zz}$ = 4e+5 N/m and $C_{xx} = C_{zz}$ = 200 Ns/m.

The critical speeds and the natural frequencies of this experimental test rig were identified using the unbalance response and the experimental frequency response function. Moreover, the FEM rotor model was fitted to the test rig where a coupling used to provide torque transmission was modelled as a bearing (Lalanne et al., 1998).

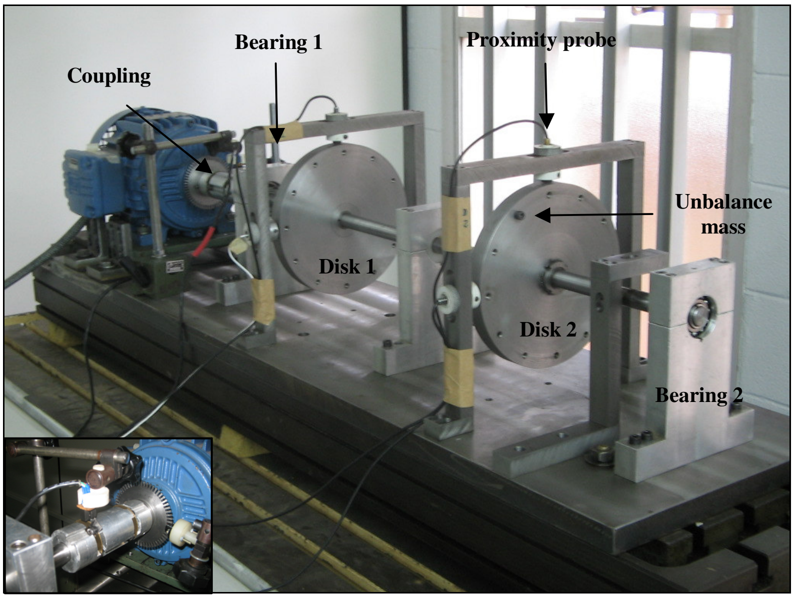

Figure 3 – Experimental test rig.

The displacements responses were measured with a pair of proximity probes located in the disks of test rig, in the horizontal and vertical direction (Fig. 3), and the rotor speed was monitored by means of an optical tachometer installed in the coupling (in detail in the Fig. 3).

Experimental results and discutions

The experimental results were accomplished in two stages. In the first, a fault by additional unbalance in the Disk 1 (Case 1) was considered, and, in the second, a fault by additional unbalance in the Disk 2 (Case 2). Moreover, the FEM model was fitted to the experimental data for a rotation below the first critical speed of the test rig (24 Hz).

In these experimental results, the adopted genetic parameters were the same ones used in the numerical simulations.

Tables 7 to 10 show the obtained results for different fault types (Case 1 and 2) and different measurement configurations.

Table 7 – Obtained results measuring in the Disk 1 and 2 in the horizontal direction (Case 1).

Design Variables (Real values)		Identified Values *(error)* *rot = 24 Hz*
m_o = 3.53e-03	(Kg)	3.5784e-03 *(+1.37%)*
e = 8.00e-2	(m)	8.1529e-02 *(+1.91 %)*
δ = 3.1416	(rad)	3.7206 *(+18.43 %)*

Table 8 – Obtained results measuring in the Disk 1 and 2 in the horizontal direction (Case 1).

Design Variables (Real values)		Identified Values (*error*) *rot = 24 Hz*
m_o = 3.53e-03	(Kg)	4.3793e-03 *(+24.05%)*
e = 8.00e-2	(m)	7.4470e-02 *(- 6.91%)*
δ = 4.7124	(rad)	4.7801 *(+1.43 %)*

Table 9 – Obtained results measuring in the Disk 2 in the horizontal and vertical direction (Case 2).

Design Variables (Real values)		Identified Values (*error*) *rot = 24 Hz*
m_o = 3.53e-03	(Kg)	3.5555e-03 *(+0.72%)*
e = 8.00e-2	(m)	8.3647e-02 *(+4.55%)*
δ = 1.5708	(rad)	1.8233 *(+16.07%)*

Table 10 – Obtained results measuring in the Disk 1 in the horizontal and vertical direction (Case 2).

Design Variables (Real values)		Identified Values (*error*) *rot = 24 Hz*
m_o = 3.53e-03	(Kg)	4.0856e-03 *(+15.73%)*
e = 8.00e-2	(m)	9.0000e-02 *(+12.50%)*
δ = 3.1416	(rad)	2.7103 *(-13.72 %)*

Analyzing the experimental results, it can be seen that the identification of searched parameters β was satisfactory, even considering a restricted number of measurements to approach of the real conditions. In the Tables 7 and 8, the difference is only the real values of the design variables, but even so the identification was satisfactory. Moreover, only the Tab. 10 presented higher errors for the three design variables, i.e. perhaps the effect of the unbalance of the disk 2 is less sensitive where only measurements on disk 1 are used.

However, displacements with larger amplitudes were experimentally observed in the vertical direction than in the horizontal direction, compared with the adopted numeric model. This probable problem of non perfect fitting between numeric and experimental should be the cause of higher errors. So, this problem will be investigated for futures studies.

CONCLUSIONS

This work presented a model based method for diagnosis of malfunction in rotor systems, where the fault parameters were formulated as an optimization problem through the method of the equivalent loads, and a genetic algorithm was implemented to search for the best estimate of these parameters. GA is one of the most robust and efficient optimization methods and it has gained recognition as a general problem solving method in many applications, mainly in solving inverse problems in rotor systems.

One of the most studied topics in research concerning to rotating machinery is the problem of rotor unbalance, and, a typical fault due to the unbalance was considered in this work.

The obtained results, both numerical and experimental, were considered as satisfactory. However, it was noticed in the experimental results, the importance of having a well adjusted model to the experiment, in other words, the quality of the fit of the model is of essential importance for the presented method.

It is important to point out also that these experimental results were the first steps of a deeper research and that more investigations should be accomplished to obtain a better identification. However, even considering a restricted number of measurements to approach of the real conditions, the results indicate that the proposed method behaved very well in the identification of the fault for unbalance, demonstrating its potentiality for application on other types of faults and to solve a wide range of inverse identification problems in a systematic and robust way.

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