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Optimal Response Amplitude in an Overhung Rotor-bearing System

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Abstract: The optimum design of a flexible rotor supported on three-lobe bearings, overhung centrifugal compressor, is studied for the optimal unbalance response using the genetic algorithm (GA) and method of feasible directions (MFD). The MFD is used to verify the GA results. The feasibility, effectivness, and avaliability of the GA is certainly of value because it allows the exploration of many different configuration of design variables and contributes to the better knowledge of design problem. There are a number of design requirements put in account for the rotor-bearing configuration that optimize the response amplitude within the operating range. These requirements are film temperature, film pressure, film thickness, power loss, lubricant flow, and stability. A rotor-bearing system must be designed to operate without excessive vibration throughout its range of operating speed.

Key words: Rotor-bearing system, unbalance response, feasible directions, genetic algorithm, optimization.

INTRODUCTION

The most commonly predicted of many important dynamic characteristic of a rotor-bearing system is unbalance response which is one of the most essential area in forced vibration analysis. The determination of unbalance response is much involved due to the asymmetry in the cross-coupled fluid film stiffness and damping coefficients which in turn is dependent on the rotor speeds. The design of the rotor-bearing system is a complicated process due to a large number of geometric and lubricant parameters. The complexity and time consuming nature of the design process of the rotor-bearing system warranted the utilizing of new methodologies which would simplify and speed up the design process. The development of faster computer has given chance for more robust and efficient optimization methods. One of these robust methods is the genetic algorithm (GA). The GA is a guided random search technique. Its parameter search procedures based on the idea of natural selection and genetics (Goldberg, 1989). It uses objective function information instead of derivatives as in gradient-based methods. Gradient-based methods are good at exploitation but not exploration of the parameter space. Since there is no exploration for all regions of parameter space, they can easily be trapped in local optima (Davis, 1991). A remarkable balance between exploration and exploitation of the search space can be made by the GA (Mitsuo and Runwie, 1997; Davis, 1991). The method of feasible directions (MFD) is used to verify the GA results.

The Problem Statement:

The aim of this study is to obtain and show the optimum peak-to-peak amplitude and mode shape of the rotor system - a typical high-speed overhung centrifugal compressor shown in Figure 1 adapted partially from (Roso, 1997)- with respect to film temperature, film pressure, film thickness, power loss, lubricant flow, and stability using the GA and the MDF. Mode shapes is used to asses the response of the rotor system to potential unbalances. The initial phase of developing a design methodology for a rotor supported in hydrodynamic bearings has been established with the modeling of the rotor-bearing system. The system consists of a large disc (impeller) at the station I, with the shaft is supported in hydrodynamic fixed three-lobe bearing, shown in Figure 2, at the station number II and III. A number of design requirements are specified and formulated as constraints which must be satisfied. The formulation for the rotor-bearing system calculation is based on a finite element method using matrix reduction method. The finite element method provides greater accuracy for a rotor discretation than other methods. Using a matrix reduction, Guyan Reduction, method in finite element based algorithm reduces the size and the computational cost of the system calculations with no significant effect on accuracy of results (Rouch, 1977; Rouch and Kao, 1980).

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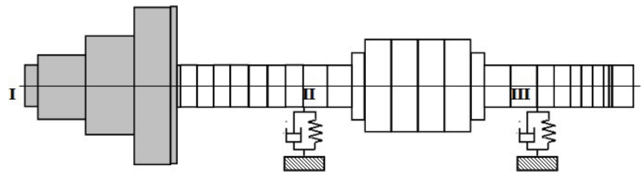


Fig. 1: The finite element model configuration of the rotor-bearing system

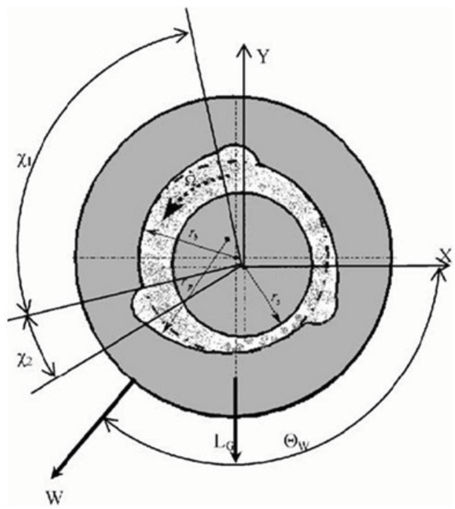


Fig. 2: Three-lobe bearing model

The finite element method has been developed to approximate the dynamic behavior of the rotor system as follows: the rotor subdivided into a finite number of elements and each element is characterized by dynamic properties. The successive assambling of the individual rotor element characterization along with the assambling of the effect due to the bearing and impeller leads to general form of equations of motion for the complete system as follows:

$$[M]\{\ddot{q}\}+[C]\{\dot{q}\}+[K]\{q\}=\{Q(t)\} \tag{1}$$

where $q=\begin{bmatrix}U_1 & V_1 & \Theta_1 & \Phi_1 & U_2 & V_2 & \Theta_2 & \Phi_2\end{bmatrix}^T$ is the vector of displacement (U V) in the X-axis and Y-axis and rotational displacement $(\Theta \quad \Phi)$ about X-axis and Y-axis, subscripts 1 and 2 identify each end of the finite element representation, and [M],[C],[K] represents the mass, damping, and stiffness matrices respectively. {Q(t)}is the vector of the exciting forces and moments. The amplitude of the rotor displacement at each nodal location is computed by first extracting the real solution from the complex results.

The sense of rotation and the semi-axes of ellipse and their disposition by introducing the complex displacements q_1 and q_2 that describe an elliptical path, which is either forward or backward in relation to the direction of rotation of the rotor, (Krämer, 1993), are:

$$R(t)=q_1(t)+jq_2(t) \tag{2}$$

$$q_1(t)=X_1\,Sin\omega t+Y_1\,Cos\omega t \tag{3}$$

$$q_2(t)=X_2\,Sin\omega t+Y_2\,Cos\omega t \tag{4}$$

$$R(t)=X_1\,Sin\omega t+Y_1\,Cos\omega t+j\,(X_2\,Sin\omega t+Y_2\,Cos\omega t) \tag{5}$$

$$R(t)=R^{+}e^{j\omega t}+R^{-}e^{-j\omega t} \tag{6}$$

$$R^{+} = (1/2)\left[(X_2 + Y_1) + j(Y_2 - X_1)\right] \tag{7}$$

$$R^{-} = (1/2)\left[(Y_1 - X_2) + j(X_1 + Y_2)\right] \tag{8}$$

where X_i, Y_i are the real and imaginary parts of the component of the eigenvector. ω is angular velocity. R^{+} is the whirl radius of the forward precession component, which is in the same direction of the rotation of the rotor, in positive direction, and R^{-} is the backward precession component which rotates in the negative direction. The maximum whirl radius, R_{max}, is defined by the major semi-axis of elliptic whirl orbit of the geometric shaft center as shown in Figure 3.

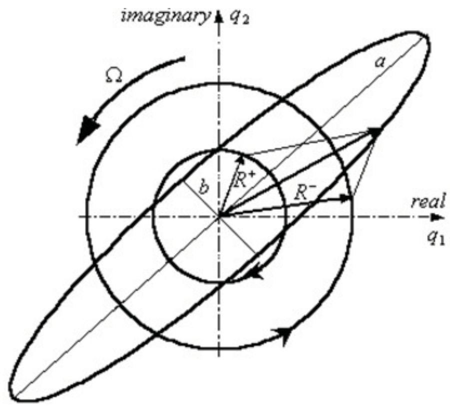


Fig. 3: Elliptical whirl orbit.

$$R_{max} = \left|R^{+}\right| + \left|R^{-}\right| = (1/2)\left[\sqrt{(X_2 + Y_1)^2 + (Y_2 - X_1)^2} + \sqrt{(Y_1 - X_2)^2 + (X_1 + Y_2)^2}\right] \tag{9}$$

From Figure 3, it can be seen that the following relations yield:

$$-1 \le (R^{+} - R^{-})/(R^{+} + R^{-}) < 0 \text{ backward whirl} \tag{10}$$

$$0 < (R^{+} - R^{-})/(R^{+} + R^{-}) \le 1 \text{ orward whirl} \tag{11}$$

$$(R^{+} - R^{-})/(R^{+} + R^{-}) = 0 \tag{12}$$

The objective function is unbalance response amplitude that aims to track the mode which exhibits the highest orbital amplitude. The statement for the objective function is:

$$F_{objective} = R_{max} = \sum_{i=1}^{Nmodes} \sum_{j=1}^{Nstations} Major\ orbit_{i,j} \tag{13}$$

where $N_{stations}$ are selected stations along the rotor where response is optimized.
The vector of design variables, X_i, include pad axial length to journal diameter ratio $(L_{axial}/(2*r_s))$ pad (lobe) arc length χ_1, bearing radial clearance c_b, pad offset factor (β/χ), pad preload factor $(c_p - c_b)/c_p)$, and bearing orientation with respect to load with the lower and upper limits expressed as follows:

$$x_1 = (L_{axial}/(2*r_s)) \qquad 0.50 \le x_1 \le 1.00 \tag{14}$$

$$x_2 = \chi_1*(\pi/(180^{\circ})) \qquad 1.50 \le x_2 \le 2.00 \tag{15}$$

$$x_3 = (c_b * (1 - ((c_p - c_b)/c_p)))/1000 \qquad 1.40 \le x_3 \le 1.95 \tag{16}$$

$$x_4 = (\beta/\chi)*2 \qquad 1.00 \le x_4 \le 2.00 \tag{17}$$

$$x_5 = ((c_p - c_b)/c_p)*2 \qquad 0.0 \le x_5 \le 1.50 \tag{18}$$

$$x_6 = \textit{Bearing orientation wrt. load} * (\pi/180^o) \qquad 0.64 \le x_i \le 2.37 \tag{19}$$

$$c_p = r_p - r_s ; c_b = r_b - r_s \tag{20}$$

where i is number of design variables and r_p,r_s, and r_b are radius of bearing pad, radius of journal, and radius of bearing at minimum bore, respectively. χ is full pad arc length, χ_2 is pad groove arc length, β is length of pad with converging film thickness, L_G is gravity load, Θ_w is resultant angle from X-axis, and W is resultant load.

Pad axial length to journal diameter ratio has effect on fluid induced instability. A key parameter used in describing fixed pad (lobe) bearings is the fraction of converging pad to full pad length. This ratio is called pad offset factor. A geometric relationship between the bearing pads and the journal can be obtained by constructing the bearing pad centers not coinciding with that of the bearing. This would produce converging and diverging film sections along each pad; consequently, fluid film pressures would be generated even with an unloaded journal. Since this condition occurs in the absence of journal load, it is called in literature as bearing preload. Because the preload can affect the shaft centerline position, the stability of the rotor system is improved. The bearing configuration parameters used in this study are journal external load (1401.2 Newton), lubricant properties (mineral base-ISO VG-32), lubricant supply pressure (1.757 kg/cm^2), and lubricant supply temperature (46.11 °C).

The conditions as constraints consisting of film temperature, film pressure, lubricant flow, stability bound, and geometric inequalities are supposed to meet the optimum design of unbalance response.

$$g_j = \begin{cases} \textit{Film temperature constraint}, \quad f_t^{lower} \le f_t \le f_t^{upper} \\ \textit{Film pressure constraint}, \quad f_p^{lower} \le f_p \le f_p^{upper} \\ \textit{Lubrication flow constraint}, \quad f_q^{lower} \le f_q \le f_q^{upper} \\ \\ \textit{Stability bound}, \quad (-\log \textit{arithmic Decrement} + 0.35) \le 0 \\ \textit{Geometric inequality}, \\ g_k(\mathrm{x}) \le 0 \qquad k = 1, 2, \ldots\ldots, NIC \text{ (number of inequality constraint)} \end{cases} \tag{21}$$

where $j = 1, \ldots\ldots\ldots NC$ (number of constraints)

Bearing temperature is an important criteria that should be met because it can be dangerous enough to give a failure in journal bearings and thus the whole system. The limit of acceptable temperature assumed is from 51.66°C to 93.33°C. The temperature rise in the lubricant is obtained by the following expression.

$$f_t = hp \,/ \left[(\textit{specific heat})(N c_b\, d_s) \right] \tag{22}$$

The rotation of the journal in the bearing results in shear losses in the lubricant film as:

$$hp = \left(\eta\, N^2 d_s^{\,3} b \right) / \left(c_b \right) \tag{23}$$

where hp is power loss, η is absolute viscosity, N is journal rotational speed, d_s is journal diameter, and b is bearing pad width. The effect of pressure in fluid film is reflected by density and viscosity of the lubricant.

If the diameter or the length of the bearing is reduced, the surface of the bearing supporting the shaft will be reduced. Thus, the higher pressure is required to be generated in the film to satisfy equilibrium. Therefore, the effect produced by the design variables requires a bound on the film pressure. The limit of acceptable film pressure assumed is from 7.03 kg/cm^2 to 87.88kg/cm^2. For the stability bound, it is required to have minimum logarithmic decrement value of 0.35 for the mode predicted to go unstable under the process fluid excitation forces. Stability analysis, namely logarithmic decrement, is necessary due to the effects of fluid forces in the rotor system. Stability is related to the solution of the damped eigenvalue problem for the rotor system.

$$\delta = -2\pi\beta_i / \omega_i \tag{24}$$

Positive values of the logarithmic decrement indicate system stability since the corresponding value of the growth factor, β_i, would be negative. The real constant ω_i represents the damped natural frequency of the system oscillation following perturbation. The logarithmic decrement can then be used to assess system stability with respect to a particular excitable mode of vibration of the rotor-bearing system.

The amount of fluid that needs to be supplied for the bearing is also a factor in bearing performance. The limit of acceptable lubricant flow assumed is from 1.0gpm and 5.0gpm . The lubricant supply groove must be adequately proportioned to host the orifice through which the lubricant is fed to the bearing. The circumferential dimension of the supply groove, along with the diameter of the orifice, has been utilized in formulating (Roso, 1997) a geometric inequality constraint, g_k (X), which would prevent the pad arc length to grow so as to not make possible the presence of an orifice of an adequate diameter.

$$g_k(x) = -\left(\frac{2\pi}{n_p} - \vartheta_p\right) + \frac{1}{r_b}\left[0.544\left(\frac{Q_s}{(1-\alpha_c)\, n_p}\right)^{0.5}\left(\frac{\gamma_i}{p_i}\right)^{0.25} + \delta_g\right] \leq 0 \tag{25}$$

where n_p is the number of lobs, ϑ_p is pad arc length in radians, Q_s is the total amount of lubricant expelled from the sides of bearing, α_c is ratio of chamfer flow to total supplied lubricant flow, γ_i is lubricant inlet density, p_i is the system lubricant pressure, and δ_g is clearance space between lubricant groove and orifice diameter.

Employing the Algorithms:

The MFD is a numerical search method which starts with an initial guess and proceeds iteratively searching through the feasible region for an optimal solution. This method was first developed by (Zoutendijk, 1960) and then modified by (Vanderplaats, 1984). The MFD is based on observation that a search direction, S_i, is found such that a small move along it would produce an improvement in the objective function value without violating the active constraints.

$$x_{i+1} = x_i + \alpha S_i \tag{26}$$

where i represents the iteration number, S the direction of movement, the scalar quantity *a* defines the distance of movement (search quantity) that must move along direction, and X_{i+1} the final point obtained at the end of S_i iteration. The choice of S_i depends on the position of point X_i. The algorithm is formulated in the following form:

Optimize $F(X_i)$ (27)

Subject to $g_j(x_i) < 0 \quad g_j(x_i) = 0 \qquad j = 1, \ldots\ldots\ldots, NC$ (28)

where $F(X_i)$ and g_J are objective and constraint functions respectively, NC is number of constraints, and X_i is a vector of design variables. Mathematically, the usability and feasibility requirement for the search direction vector, S, can be expressed as follows:

$\nabla F(x_i)\, S \leq 0$ usability $\quad \nabla g_j(x_i)\, S \leq 0$ easibility (29) where $\nabla F(x_i)$ is the gradient of the objective and $\nabla g_j(x_i)$ is the gradient of the jth active constraint computed at point X_i. Reader can refer to detailed information about this method by (Vanderplaats, 1984). The GA is first proposed by (Holland, 1975) and extended further by (De Jong, 1975) and (Goldberg, 1989). The GA is an efficient search technique which applys the rules of natural genetics to explore a given search space (Homaifar *et al*., 1994). The GA is well behaving to problems with complex, discontinues, and discrete functions. The GA maintains a population of encoded solutions, and guides them towards the optimum solution (Goldberg, 1989). Thus, it searches the space of possible individuals and seeks to find the fittest string. Rather than starting from a single point solution within the search space as in numerical methods, the GA is started with an initial set of random solutions. The solutions are represented by strings, namely chromosomes which are coded a series of zeros and ones.

The description of the genetic algorithm is outlined in Figure 4. The genetic algorithm starts with a certain number of initial population numbers with random conbinations of 0s and 1s and the fitness of each individual in initial population members is evaluated. The algorithm then proceeds by generating new design until the termination criteria have been satisfied. After the evaluation of each-individual fitness in the population, the genetic operators, selection, crossover, and mutation, are applied to produce a new generation. Other genetic operators are applied as needed. The newly created individuals replace the existing generation, and re-evaluation is started for fitness of new individuals. In each succeeding generation, the genetic algorithm creates a new set of chromosomes using best information of previous generation. The loop is repeated until an acceptable solution is found.

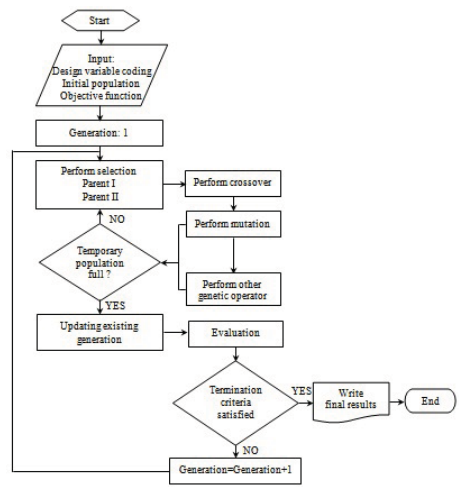


Fig. 4: Flow chart of the genetic algorithm.

In the GA, fitness function measures and rates the coded variable vectors in order to select the fittest strings that lead the solution. Constraint optimization problem have been transformed into an unconstrained optimization problem and handled by penalizing the objective function value by, for this study, a unique static penalty function proposed in (Homaifar *et al*., 1994). In case of any violation of a constraint boundary, the fitness function of corresponding solution is penalized and kept within feasible regions of design space. For controling of the penalization process, penalty cooefficients, r_j , used for different level of violation of each constraint. The penalty coefficients have to be judiciously selected, (Homaifar *et al*., 1994), because the reasonable solutions importantly depends on values of these coefficients.

$$Fitness\ Function = \sum_{i=1}^{N\ nodes} \sum_{j=1}^{N\ stations} Major\ orbit_{i,j} + \sum_{j=1}^{NC} r_j \left(\max\left[0, g_j\right] \right)^2 \tag{30}$$

where NC is number of constraints.

Each design variable has a specified range so that $x(i)_{lower} \leq x(i) \leq x(i)_{upper}$ The continuous design variables vector are represented and discretized to a precision of ($\Delta x = 0.01$ The number of digits in the binary string, L, is estimated from the following relationship (Lin and Hajela, 1992):

$$2^L \geq \left[\left(x(i)_{upper} - x(i)_{lower} \right) / \Delta x \right] + 1 \tag{31}$$

where $x(i)_{lower}$ and $x(i)_{upper}$ are the lower and upper bound for design variables vector respectively.

The six design variables are coded into binary digits {0, 1} as shown in Table 1. The binary string representation for the vector of design variables, x(i), can be placed head-to-tail to form one long string, referred to as a chromosome. This chromosome represents a solution to the design problem. Table 2 shows string of 42 binary digits denotes the concatenated design variables vector. A randomly selected set, for this study a 50-string, of potential solutions is initialized to form the starting population. The real value of the design variable vectors can be transformed from binary string by following relationship (Wu and Chow, 1995).

$$x(i) = \left[\left(x(i)_{upper} - x(i)_{lower} \right) / \left(2^{L} - 1 \right) \right] a(i) + x(i)_{lower} \tag{32}$$

where a(i) represents the decimal value of string for design variables vector which is obtained by using base-2 form.

Table 1: Coding of design variables vector into binary digits

Design Variables Vector	Lower Limit	Upper Limit	Binary String	String Length	Decoded Value
x(1)	0.50	1.00	0 1 0 1 0 0	6	0.658
x(2)	1.50	2.00	0 1 0 1 0 0	6	1.658
x(3)	1.40	1.95	1 0 1 0 0 1 1	7	1.759
x(4)	1.00	2.00	0 0 1 0 0 0 1	7	1.133
x(5)	0.00	1.50	0 0 1 0 1 0 1 0	8	0.247
x(6)	0.64	2.37	1 0 0 0 1 0 0 1	8	2.247

Table 2: A set of starting population

	Initial Population Concatenated variables vectors head-to-tail					
	x(1)	x(2)	x(3)	x(4)	x(5)	x(6)
	010100	010100	1010011	0010001	00101010	10001001
1	10 1 0 1 0 0 0 1 0 1 0 0 1 0 1 0 0 1 1 0 0 1 0 0 0 10 0 1 0 1 0 1 0 1 0 0 0 1 0 0 1					
	100111	100010	0100101	1100011	10101010	01110110
2	1 0 0 1 1 1 1 0 0 0 1 0 0 1 0 0 1 0 1 1 1 0 0 0 1 11 0 1 0 1 0 1 0 0 1 1 1 0 1 1 0					
.	.	.	.	.	.	.
	001101	0111000	1001100	0011100	00011001	10001010
50	0 0 1 1 0 1 0 1 1 1 0 0 01 0 0 1 1 0 00 0 1 1 1 0 00 0 0 1 1 0 0 11 0 0 0 1 0 1 0					

Succesive populations are produced by the operations of selection, crossover, and mutation. The selection operator determines those member of the population that survive to participate in the forming of members of next generation. Design vector with better fitness values are more likely to survive and be chosen as parents for the successive generation. There are many methods to perform the selection. The selection operator used in the algorithm code is a tournament selection with a shuffling technique for choosing random pairs for mating. Shuffling technique rearrange the population in random order for selection. Tournament selection approach works as follows: a pair of individuals from mating pool is randomly picked and the best-fit two individuals from this pair will be chosen as a parent. Each pair of parent creates two Child as described in the method of uniform crossover , used in this study, shown in Table 3. The algorithm is based on elitist reproduction strategy. Elitism forces the genetic algorithm to retain the best individual in a given generation to proceed unchanged into the following generation (Mitchell, 1997). This ensures the genetic algorithm to converge to appropriate solution. In other words, elitism is a safeguard against operation of crossover and mutation that may jeopardize the current best solution.

A uniform crossover probability of 0.5 is recommended in many works such as(Spears and De Jong , 1991) and (Syswerda, 1989). This operator is primary source of new candidate solutions and provides the search mechanism that efficiently guides the evolution through the solution space towards the optimum. In uniform crossover, every bit of each parent string has chance of being exchanged with corresponding bit of the other parent string. Procedure is to obtain any combination of two parent strings (chromosomes) from the mating pool randomly and generate new Child strings from these parent strings by performing bit-by-bit crossover chosen according to a randomly generated crossover mask (Beasley *et al*., 1993). Where there is a "1" in the crossover mask, the child bit is copied from the first parent string, and where there is a "0" in the mask, the Child bit is copied from the second parent string. The second Child string uses the opposite rule to the previous one as shown in Table 3. For each pair of parent strings a new crossover mask is randomly generated.

Table 3: Uniform crossover

Crossover mask	100101110010010111001001011100100101110010
Parent 1	101000111010100011101010001110101000111010
Parent 2	010101001101010100110101010011010101001101
Child 1	110000111111000011111100001111110000111111
Child 2	001101001000110100100011010010001101001000

Preventing the genetic algorithm from premature convergence to a non-optimal solution, which may diversity lost by repeated application of selection and crossover operators, mutation operator is used. Mutation is basically a process of random altering a part of individual to produce a new individual by switching the bit position from a 0 to a 1 or vice versa. The jump mutation operator is used in this study. The jump mutation produces a chromosome which is randomly picked to be in the range of appropriciate parameter. Mutation probabilities of 0.001, 0.01, and 0.1 were tested for genetic algorithm performance. The result showed that the mutation probability of 0.001 gives preferable results compared to 0.1 and 0.01. It should be noted that if a mutation rate a 0.1 is selected, many good strings are never evaluated. In other words many random perturbations are happened with mutation rate 0.1. This causes the losing of parent resemblance and is disastrous for obtaining the optimum point. There are many different ways to stop running the genetic algorithm one method is to stop after a present number of generations which is used in this study. Convergence is the progression toward uniformity. The setting parameters of genetic algorithm for this study are chosen as follows: Chromosome length = 42, population size = 50, number of generation = 77, crossover probability = 0.5, mutation probability = 0.001

RESULTS AND CONCLUSIONS

The optimization algorithms are repeated until no search direction can be found that will improve objective function without violating the constraints. Figure 5 shows the plots of the normalized avarage and best fitness function values by the GA in each generation as optimization process proceeds. The GA found the results at generation number 53 (2650 function evaluations), while the MFD at 776 function evaluations.

The comparison of the amplitude and angle variation for station I, II, and III with respect to the horizontal directions for both methods represented in Figure 6. The ordinate is the peak-to-peak amplitude and the operating speed range from 1150 rpm to 40000 rpm. The maximum response peaks are introduced for the MFD approximately 0.64 mils peak-to-peak at station I, 0.42 at station II, and 0.12 at station III while for the GA approximately 0.29 mils at station I, 0.23 at station II, and 0.14 at station III. There is resonable agreement between the both methods in the magnitudes of the responses through running speeds although the magnitude of the response amplitude by the GA is much smaller.

The GA ended for logarithmic decrement with 1.11 while the MFD with 0.41. This significant outcome allows the rotor to maintain stability. As can be seen in Table 4, the GA obtained lower film temperature and power loss, and higher film thickness and fim pressure when compare to the MFD. The results at operating speed of 28000 rpm from the GA showed that film temperature ended with 69.4 ^{o}C while the MFD with 93.3 ^{o}C, the power loss ended with 3.73 hp while the MFD with 4.35 hp, the film thickness ended with 0.03309 mm while the MFD with 0.02819 mm, and film pressure ended with 49.13 kg/cm^2 while the MFD with 59.87 kg/cm^2. The effect of a thin minimum film thickness causes high temperature in the lubricant film. The design variables are all systematically vary to identify the effects of each combination finding the minimum objective function along design criteria. Thus, (see Table 4), radial clearance increase as the minimum film thickness increases, power loss decreases by reducing the length of the bearing pads, an increase in journal diameter would produce increase in losses, the maximum pad peak pressure is reduced to minimum values by increasing the axial length of bearing pad, and the instability treshold increases with larger preloads while tends to decreases as the offset factor increases. The deflection form of the shaft at natural frequency, called the mode shapes, for the corresponding forward (FW) and backward (BW) modes are given in Figure 7 and Figure 8.

Table 4: Comparison of the best overall solution found by the MFD and the GA.

	MFD	GA
Radius of journal, mm	20.6375	20.6375
Pad axial length, mm	35.5033	22.2752
Pad arc length, deg.	109.3	93.8
Bearing radial clearance, mm	0.036449	0.036576
Pad offset factor	0.7428	0.5039
Pad preload factor	0.5069	0.1029
Bearing orientation, deg.	128.07	58.82
Minimum film thickness, mm	0.0282	0.0330
Maximum film temperature, ^{o}C	93.33	69.98
Maximum film pressure, Kg/cm^2	49.13	59.87
Power loss, hp	4.353	3.73
Required lubricant flow, gpm	0.86	2.29

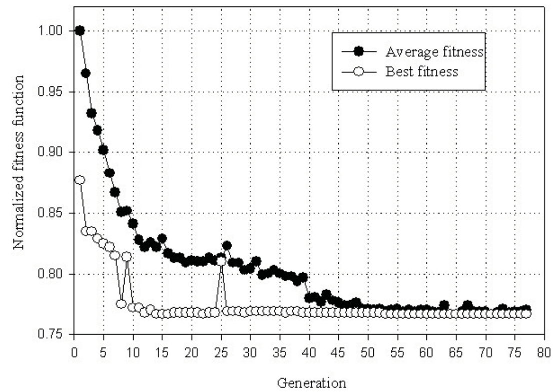


Fig. 5: Convergence process of the genetic algorithm for the best and average fitness function

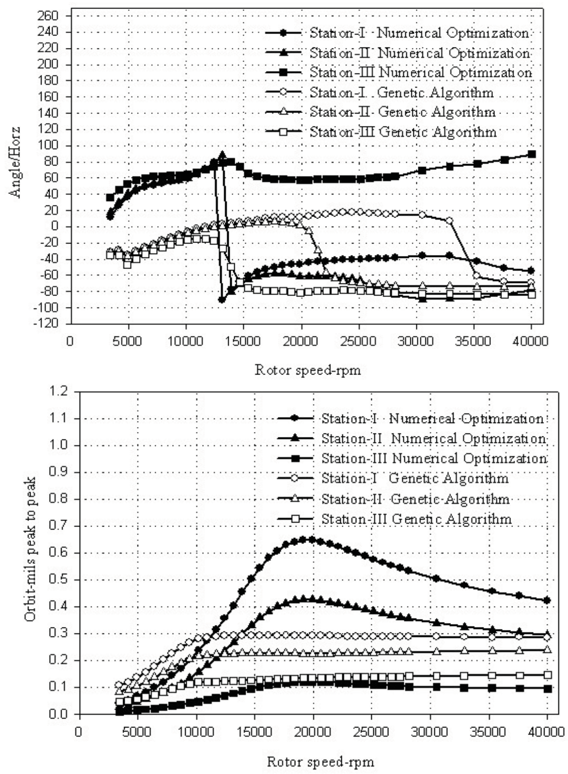
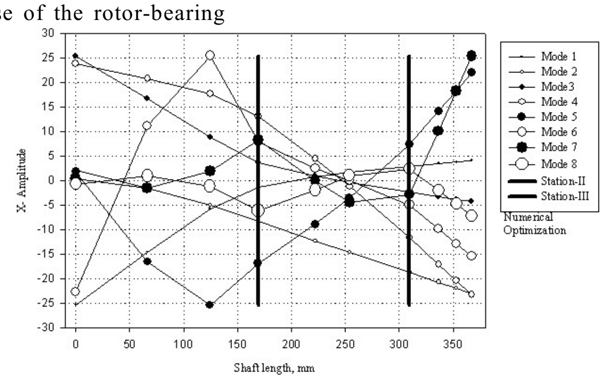


Fig. 6: unbalance response of the rotor-bearing



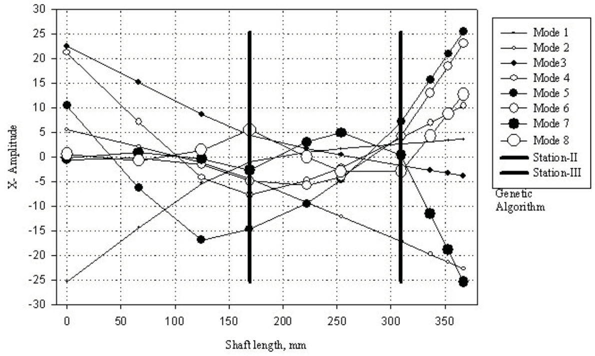


Fig. 7: Mode shapes for the shaft in X-direction

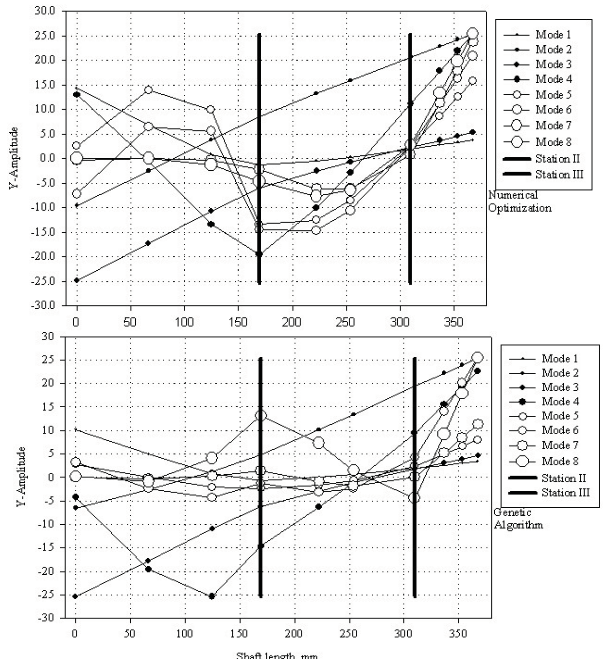


Fig. 8: Mode shapes for the shaft in Y-direction

Conclusions:

In this study, a finite element based computer code was coupled to the GA and the MFD to extract more accurately needed information about the amplitude of motion of the rotor-bearing system. Using the finite element method with the GA in the problem at hand requires a significant amount of memory storage compare to the MFD. This requires more computational effort. However, this disadvantage is not significant with the current computing capability. The GA was able to obtain better results than those obtained by MFD. The feasibility, effectivness, and availability of this robust optimization technique is certainly of value because it allows the exploration of many different configurations of design variables and therefore also contributes to the better knowledge of the rotor and bearing behavior in general.

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