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Design Optimization of Tilting-Pad Journal Bearing Using a Genetic Algorithm

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This article focuses on the use of genetic algorithms in developing an efficient optimum design method for tilting-pad bearings. The approach optimizes based on minimum film thickness, power loss, maximum film temperature, and a global objective. Results for a five tilting-pad preloaded bearing are presented to provide a comparison with more traditional optimum design methods such as the gradient-based global criterion method, and also to provide insight into the potential of genetic algorithms in the design of rotor bearings. Genetic algorithms are efficient search techniques based on the idea of natural selection and genetics. These robust methods have gained recognition as general problem solving techniques in many applications.

Keywords Genetic algorithm, Global optimum, Optimization, Tilting-pad journal bearing

Many numerical optimization methods have been developed and used for design optimization of journal bearings. Most of these methods are based on gradient techniques. These methods are reasonably effective for well-behaved objective functions. This is because the gradient of the function helps to guide the direction of the search. However, when the continuity and existence of derivatives of the function are not assured, gradient methods lack robustness and may trap in local optima. To overcome these problems, many different approaches exist in the literature. The development of faster computers has allowed development of more robust and efficient optimization methods. One of these robust methods is the genetic algorithm, which has gained recognition as a general problem solving technique in many applications. The genetic algorithm is a guided random search technique. It uses objective function information, instead of derivatives as in gradient-based methods.

Numerical search techniques are good at exploitation but not exploration of the parameter space. They focus on the area around the current design point, using local gradient calculations to move to a better design. Since there is no exploration for all regions of parameter space, they can easily be trapped in local optima (Davis, 1991). Genetic algorithms are a class of general-purpose algorithms that can achieve a "remarkable balance between exploration and exploitation of the search space" (Mitsuo and Runwei, 1997). The genetic algorithm is new to the field of journal bearing analysis, and in current literature there is limited work in the area of rotor-bearing system using genetic algorithms. Interested readers can refer to the studies by Crossley et al. (1995), Crossley (1996), Choi and Yang (1998), Choi (1999), and Saruhan et al. (2001).

GENETIC ALGORITHMS

Genetic algorithms are efficient search techniques which are inspired from the natural genetics selection process to explore a given search space (Homaifer et al., 1994). Genetic algorithms are being applied successfully to find solutions to problems in business, engineering, and science (Goldberg, 1994). These robust adaptive searching techniques have gained recognition as general problem solving techniques in many optimization problems. Genetic algorithms maintain a population of encoded

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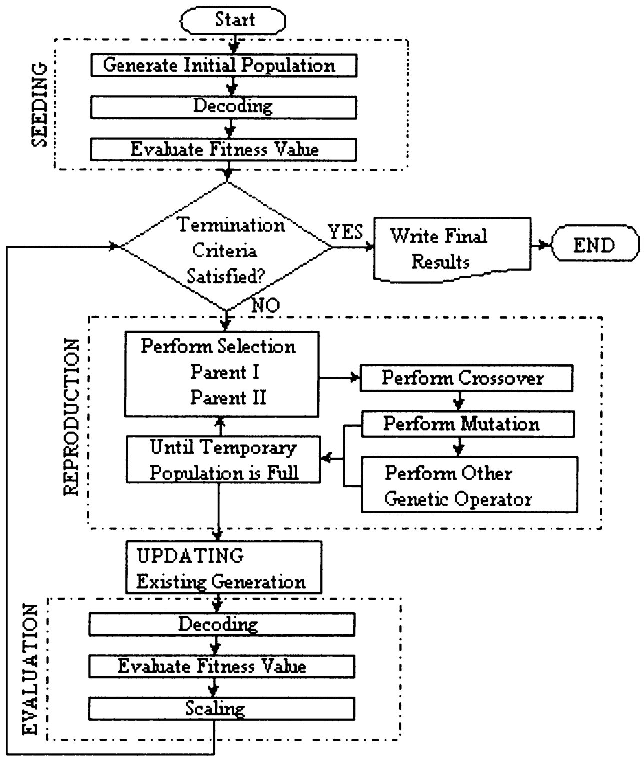

FIGURE 1
Flow chart for a simple genetic algorithm.

solutions, and guide the population towards the optimum solution (Goldberg, 1989). Thus, they search the space of possible individuals and seek to find high-fitness string. Rather than starting from a single point solution within the search space as in traditional methods, genetic algorithms are initialized with a population of a solution. Viewing the genetic algorithms as optimization techniques, they belong to the class of zero-order optimization methods (Dracopoulos, 1997) which require only function evaluations.

The flowchart of a simple genetic algorithm is outlined in Figure 1. An initial population is chosen randomly in the beginning, and fitness of initial population members is evaluated. Then an iterative process starts until the termination criteria have been satisfied. After the evaluation of each individual fitness in the population, the genetic operators of 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. The loop is repeated until an acceptable solution is found.

PROBLEM STATEMENT

The effort in this study is the use of the Genetic Algorithm Method in the optimum design of a five tilting-pad bearing, shown in Figure 2 for a rotor system, and developing the bearing configurations that optimize minimum film thickness, power loss, maximum film temperature, and global objective. Due to the assumption of lightweight pads considered in this study, the main objectives will be film thickness, power loss, and maximum film temperature. Tilting-pad hydrodynamic bearings result in a more stable rotor-bearing system since there is no significant cross-coupling between coordinates under symmetric load conditions (Knight, 1990).

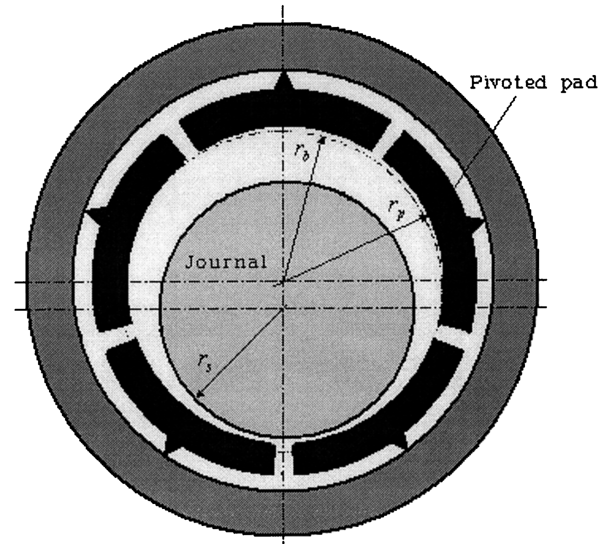

FIGURE 2
Schematic diagram of symmetrical five tilting-pad bearing.

In the course of the development of high-speed tilting pad bearings a wide variety of phenomena have been studied and investigated. Since it is not the intent of this article to provide a review of tilting-pad bearing literature, the reader can refer to some of the studies by Lund (1964), Nilsson (1978), Nicholas et al. (1979), Allaire (1979), Rouch (1982, 1983), Lundand Pederson (1987), and Kirk and Reedy (1988).

The first step in any optimization process is the formulation of the design problem. The main goal is either to maximize or minimize design objectives, and satisfy imposed constraints. Design variables are the numerical quantities that affect the objective value, and are to be chosen in an optimization problem. These variables are the main factor in determining the design problem.

Design Variables

The design vector of variables included pad axial length to journal diameter ratio, pad arc length, pad offset factor, pad preload factor, and bearing radial clearance expressed as:

$$x(i) = \begin{cases} \textit{Pad axial length/Journal diameter} \\ \textit{Pad arc length} \\ \textit{Bearing radial clearance} \\ \textit{Pad offset factor} \\ \textit{Pad preload factor} \end{cases} \qquad [1]$$

where $i = 1, \ldots\ldots\ldots NDV$

Pad axial length to journal diameter ratio has an effect on fluid induced instability. It also plays a role in the load capacity. When the ratio is increased the capacity of carrying load is increased. One of the key parameters used in describing tilting pad bearings is the fraction of converging pad to full pad length. This ratio is called *pad offset factor* and is defined as (Hamrock, 1991):

$$\alpha_p = \frac{\textit{Length of pad with converging film thickness}}{\textit{Full pad arc length}} \quad [2]$$

With increasing bearing pad offset factor, the pad pivot position moves from the center of the pad toward the trailing edge. It is a common practice in industry to provide journal pads with preload. The relationship between two clearances c_b and c_p, namely bearing radial clearance and bearing pad clearance, is defined as preload. c_p is the difference of the radius of curvature of the pad, r_p, and journal radius, r_s. Preload factor (Rouch, 1983) can be expressed as:

$$\textit{Pad preload factor} = 1 - \frac{c_b}{c_p} \quad [3]$$

where c_p and c_b can be computed as:

$$c_p = r_p - r_s; \quad c_b = r_b - r_s \quad [4]$$

State Variables

State variables are the physical quantities, which vary with the given operating conditions of the journal bearing. These parameters are journal unbalance, lubricant properties, lubricant pressure, and lubricant temperature.

Constraints

Constraints are conditions that must be met in the optimum design and include restrictions on criteria functions. Constraints used in this study are as follows:

$$g_j = \begin{cases} \textit{Film temperature constraint}, \quad f_t^{lower} \le f_t \le f_t^{upper} \\ \textit{Film pressure constraint}, \quad f_p^{lower} \le f_p \le f_p^{upper} \\ \textit{Lubrication flow constraint}, \quad f_q^{lower} \le f_q \le f_q^{upper} \\ \textit{Orbital displacement constraint}, \quad f_u^{lower} \le f_u \le f_u^{upper} \\ \textit{Stability parameter constraints} \\ \textit{Geometric inequality}, \\ g_k(\mathrm{x}) \le 0 \quad k = 1, 2, \ldots\ldots, NIC \end{cases} \quad [5]$$

Objective Functions

The objective function is a quantity to be minimized or maximized by exploring a search space under the imposed constraints, for example:

$$F_{objective} = \begin{cases} \textit{Minimum film thickness objective}, h^* \\ \textit{Power loss objective}, hp^* \\ \textit{Maximum film temperature objective}, t^* \end{cases} \quad [6]$$

The global statement of the optimization algorithm for a multi-objective function for journal bearing can be represented by:

$$Fitness_{Global} = w_1 F_1 + w_2 F_2 + w_3 F_3 + \sum_{j=1}^{NCON} r_j (\max[0, g_j(x)])^2 \quad [7]$$

where,

$$F_1 = \left(\frac{f_h(x) - h^*}{h^*}\right)^2, \quad F_2 = \left(\frac{f_{hp}(x) - hp^*}{hp^*}\right)^2,$$

$$F_3 = \left(\frac{f_t(x) - t^*}{t^*}\right)^2 \quad [8]$$

$$\sum_{i}^{NOBJ} w_i = 1 \quad i = 1, \ldots . NOBJ \quad [9]$$

$$0 \le w_i \le 1 \quad [10]$$

Weight coefficients, w_i, are used in order that each individual objective function would contribute proportionally to the fitness value. The constraint optimization problem has been transformed into an unconstrained optimization problem and handled by penalizing the objective function value by quadratic penalty function, which is used to ensure that the journal bearing meets any imposed constraints, represented in Equation (7). The penalty coefficients, r_j, for the j-th constraint have to be judiciously selected because the solutions depend on proper values of penalty coefficients. The individual optimization values, h^*, hp^*, t^*, are obtained from sub-optimization of each objective function by running the genetic algorithm using Equation (11) for maximization and Equation (12) for minimization. These individual functions also include the corresponded quadratic penalty function.

$$Fitness_{Objective} = F_i - \sum_{j=1}^{NCON} r_j (\max[0, g_j(x)])^2 \quad [11]$$

$$Fitness_{Objective} = F - \left(F_i + \sum_{j=1}^{NCON} r_j (\max[0, g_j(x)])^2\right) \quad [12]$$

where F_i is $f_h(x)$, $f_{hp}(x)$, $f_t(x)$, and F is a positive number which has to be large enough to exclude negative fitness values (Goldberg, 1989).

Construction of Design Variables

The continuous design variables vector are represented and discretized to a precision of ε ($\varepsilon = 0.01$) as a "binary string."

TABLE 1
Coding of design variable vectors into binary alphabet

Design variables vectors		Randomized binary digits	l
Pad axial length/journal diameter	$x(1)$	0 1 0 1 0 0	6
Pad arc length	$x(2)$	0 1 0 1	4
Bearing radial clearance	$x(3)$	1 0 1 0 0 1 1	7
Pad offset factor	$x(4)$	0 0 1 0 0	5
Pad preload factor	$x(5)$	0 0 1 0 1 0	6

The number of digits in the binary string, l, is estimated from the following relationship (Lin and Hajela, 1992):

$$2^l \geq [(x(i)_{upper} - x(i)_{lower})/\varepsilon] + 1 \qquad [13]$$

where $x(i)_{lower}$ and $x(i)_{upper}$ are the lower and upper bound for the design variables vector, respectively. Suitable representation, coding, of the design vectors is a key to success in using genetic algorithm. The design vector of variables is coded into binary digits $\{0, 1\}$ as shown in Table 1. The binary string representation for the vector of 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 a string of 28 binary digits, which denotes the concatenated design variables, $x(i)$, vector. This single 28-bit string represents one of the 2^{28} alternative existent solutions in the design search space.

The genetic algorithm begins with an initial population of chromosomes. A set, 40 strings for this study, of potential solutions is initialized to form the starting population as can be seen in Table 3.

The parameters of the genetic algorithm for this study are chosen as follows: chromosome length = 28; population size = 40; number of generations = 100; crossover probability = 0.5; mutation probability = 0.001.

The selection scheme used in the algorithm code is a tournament selection with a shuffling technique for choosing random pairs for mating. The shuffling technique rearranges the population in random order for selection. A specialized mechanism, *elitism*, is added to the genetic algorithm. Elitism forces the genetic algorithm to retain the best individual in a given generation, to proceed unchanged into the following generation (Mitchell, 1997). This helps ensure that the genetic algorithm converges to an appropriate solution. In other words, elitism is a safeguard against operation of crossover and mutation operators that may jeopardize the current best solution. A uniform crossover operator is used in this study. A uniform crossover probability of 0.5 is recommended in many works such as Syswerda (1989), and Spears and De Jong (1991). Crossover is very important in the success of genetic algorithms. This operator is a 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 a chance of being exchanged with the corresponding bit of the other parent string. The procedure is to obtain any combination of two parent strings (chromosomes) from the mating pool at random and generate new child strings from these parent strings by performing bit-by-bit crossover chosen according to a randomly generated crossover mask (Beasly 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 Figure 3. For each pair of parent strings a new crossover mask is randomly generated.

By preventing the genetic algorithm from premature convergence to a nonoptimal solution, which may lose diversity by repeated application of selection and crossover operators, the mutation operator is used. Mutation is basically a process of randomly altering a part of an individual to produce a new

TABLE 2
Binary string representation for the vector of variables

Concatenated variables vectors head-to-tail					Total bits length
$x(1)$	$x(2)$	$x(3)$	$x(4)$	$x(5)$	28
010100	0101	1010011	00100	001010	...010011001...

TABLE 3
A set of starting population

Individual number	Initial population				
	$x(1)$	$x(2)$	$x(3)$	$x(4)$	$x(5)$
1	010100	0101	1010011	00100	001010
	0101000101101001100100001010				
2	100111	1000	0100101	11000	101010
	1001111000010010111000101010				
.	.				
.	.				
.	.				
.	.				
40	001101	0111	1001101	00111	000110
	0011010111100110100111000110				

Crossover mask	1001011100100101110010010111
Parent 1	**1010001110101000111010100011**
Parent 2	0101010011010101001101010100
Child 1	1100001111110000111111000011
Child 2	0011010010001101001000110100

FIGURE 3
Uniform crossover.

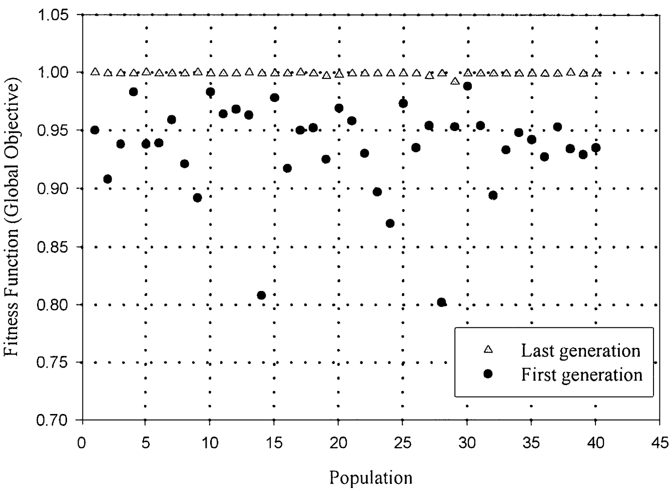

FIGURE 4
Distribution of normalized fitness function values for first and last generation.

individual, by switching the bit position from a 0 to a 1 or vice versa. This operator explores new possibilities for solution but should be selected carefully in order to not cause loss of good characteristics of strings. Mutation probabilities of 0.001, 0.01, and 0.1 were tested for genetic algorithm performance. The results showed that the mutation probability of 0.001 gives preferable results compared to 0.1 and 0.01. The mating process helps the genetic algorithm explore the search space by making use of the bit combinations already assigned in the string.

RESULTS

The distribution of normalized fitness function values for the global objective in the first and the last generations of a sample case are given in Figure 4. Figure 5 shows the plots of the normalized average and best fitness function values in each generation as optimization proceeds. The results show that the best designs rapidly improve to converge over the first several generations and refine the design over remaining generations. The genetic algorithm found the optimal film thickness, power loss, film temperature, and global optimum at generations 18, 21, 44, and 16, respectively. As can be seen in Figure 5, a form of uniform convergence with a fair percentage is observed.

Comparison of the best overall solution found with numerical optimization by Roso (1997) and genetic algorithm technique is given in Tables 4 and 5. The results of sub-optimization of each objective function and global objective for both methods are presented. As can be seen from these results, the genetic algorithm was able to obtain better results than those obtained by numerical optimization. Although the value of power loss and temperature obtained in global optimum with genetic algorithm are slightly higher than those obtained with numerical optimization, the overall performance of the bearing is much better.

Using the idea of the penalty function method in the genetic algorithm is to punish the fitness value of the design variables whenever the solution violates the constraints assigned for the design problem. In numerical optimization the bound on the constraints is tighter than that imposed by genetic algorithm. This difference in the procedure may cause the solutions to differ, as is noted for the preload.

TABLE 5
Comparison of the best overall solution found for optimized geometry of bearing for global objective by numerical and genetic algorithm optimization

	Optimization method	
Bearing optimized geometry	Numerical optimization	Genetic algorithm
Global optimization		
Number of pads	5	5
Number of orifices	2	2
Radius at minimum bore, in	0.8152	0.8151
Pad axial length, in	1.1042	1.2896
Pad arc length, °	57.4	61.99
Orifice(s) diameter, in	0.1250	0.1250
Bearing radial clearance, in	0.00267	0.00264
Pad clearance, in	0.00612	0.00357
Pad offset factor	0.518	0.510
Pad preload factor	0.564	0.261
Bearing orientation, °	52.0	53.4

TABLE 4
Comparison of the best overall solution found for each of individuals and global objective by numerical and genetic algorithm optimization

	Numerical optimization		Genetic algorithm	
Objective functions	Individual	Global	Individual	Global
Minimum film thickness	0.00152	**0.00122**	0.00154	0.00138
Power loss	2.82	**3.64**	2.78	3.90
Maximum film temperature	155.3	**165.9**	154.1	171.5

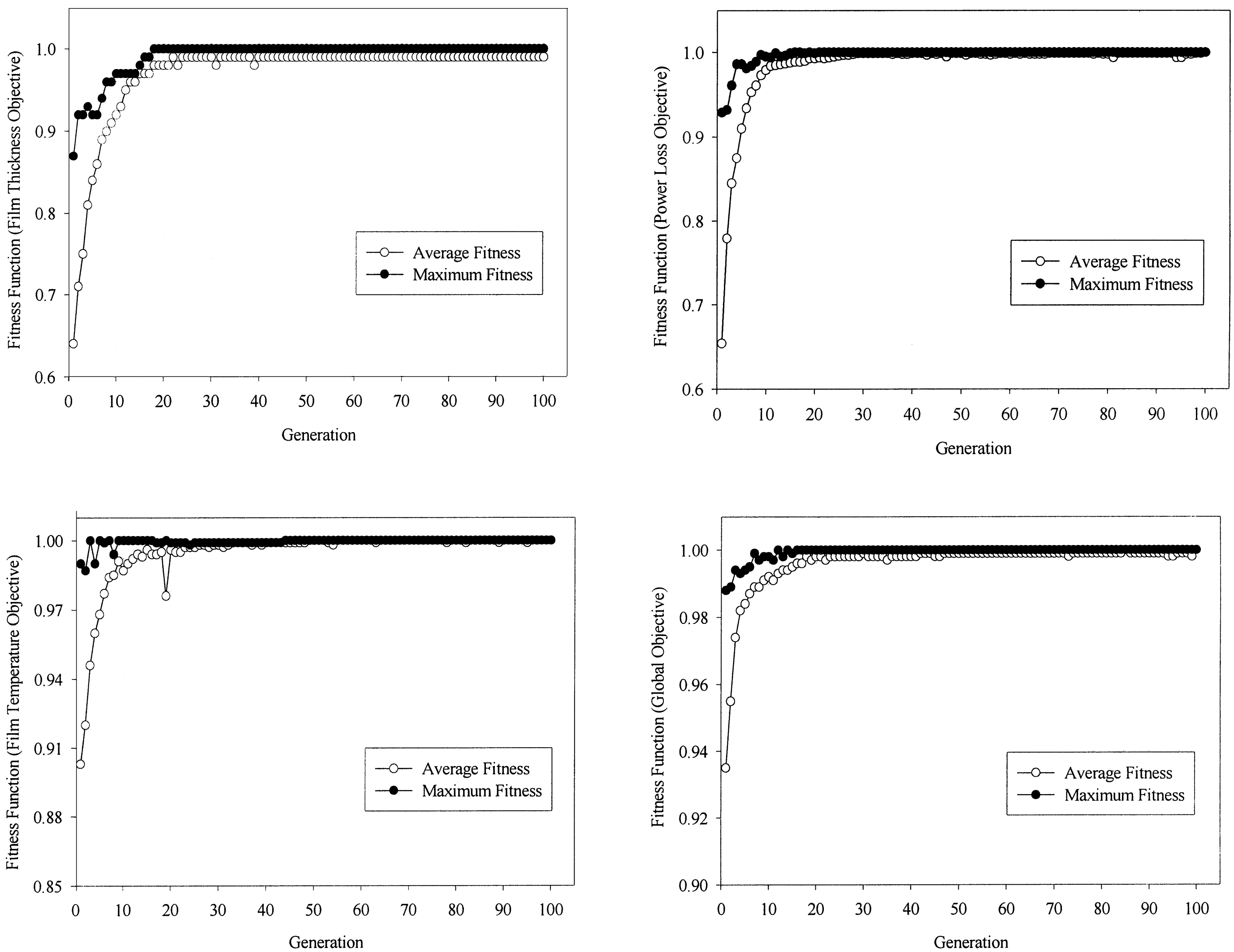

FIGURE 5
Convergence process of genetic algorithm for normalized best and average fitness function of function objectives (film thickness, power loss, film temperature, and global objective).

CONCLUSIONS

The purpose of this study was to implement an optimization approach of a tilting-pad journal bearing using a genetic algorithm, and compare the results with more traditional optimization methods. The study showed the feasibility and effectiveness of the genetic algorithm. This algorithm produced good results for both individual objective functions and a global objective. The results are comparable to those from gradient-based optimization method.

Analysis of the tilting-pad bearing is complicated due to multiple movable pads. Because of this, the mutation probability rate used in the algorithm must be carefully selected. Too high a mutation probability rate can result in failure of bearing design during program solution by causing one of the pads to touch the journal. Thus, when a high mutation rate is selected, many random perturbations can happen. This causes the loss of parent resemblance.

The genetic algorithm requires a greater number of function evaluations than numerical method. This requires more computational effort. However, this disadvantage is not significant considering the current computing capability.

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NOMENCLATURE

c_b bearing radial clearance
c_p bearing pad clearance

f_h	film thickness
f_{hp}	power loss
f_p	film pressure
f_q	lubricant flow
f_t	film temperature
f_u	orbital displacement
F	positive constant
h^*	film thickness objective
hp^*	power loss objective
g_i, g_k	constraints
l	chromosome length
Log.Decr	logarithmic decrement
NCON	number of constraints
NDV	number of design variables
NIC	number of inequality constraints
NOBJ	number of objectives
r_b	bearing radius
r_j	penalty coefficients
r_p	radius of curvature of pad
r_s	journal radius
t^*	film temperature objective
w_i	weight coefficients
$x(i)$	variables vector
ε	precision
ε_s	user defined constant
α_p	pad offset factor

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