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Optimization of Principal Dimensions of Radial Flow Gas Turbine Rotor Using Ant Colony Algorithm

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Abstract: The gas turbine is the most versatile item of turbo machinery today. It can be used in several different modes in critical industries such as power generation, oil and gas, process plants, aviation, as well domestic and smaller related industries. The choice of the principal dimensions of a turbine rotor for a given set of inlet design specifications can be found by solving aerodynamic equations. An analytical method is indeed difficult and can be very time consuming, especially if the complete procedure has to be repeated for different cases. In this paper, we propose a novel feature selection algorithm ant colony optimization (ACO) for faster and better search capability. Proposed algorithm is easily implemented and because of use of a simple classifier in that, its computational complexity is very low. The performance of proposed algorithm is compared to the performance of Genetic algorithms.

Keywords: Ant colony optimization, Genetic algorithm, Local search, Metaheuristics

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1. INTRODUCTION

Gas turbines are one of the key energy producing devices of Power generation. A radial turbine stage is differential form an axial turbine stage by having the fluid undergo a significant change in passing through the rotor [1]. The preliminary design and analysis procedure allows the key turbine dimensions to be specified and the performance predicted at an early stage [2]. Complete design of the inward flow radial (IFR) turbine rotor requires the aero-thermodynamic, structural and manufacturing criteria to be satisfied simultaneously. The design specifications normally include the mass flow rate of the working fluid, pressure ratio, and in some cases, rotational speed [3]. Radial turbine design is dictated by criteria like specific speed and/or velocity ratios. For small capacity plants the size of the turbine wheel needs to be reduced and thus the rotational speed increased in order to reach a high efficiency [4]. The choice of the principal dimensions of a turbine rotor for a given set of inlet design specifications can be found by solving aerodynamic equations. An analytical method is indeed difficult and can be very time consuming, especially if the complete procedure has to be repeated for different cases. In view of this, numerical optimization techniques can be a useful tool to problems involving a large number of variables [4]. The freedom of the choice of tip diameter and the tip width of the rotor that would be necessary for optimum isentropic optimization procedure will be a useful tool to determine the principal dimensions of the rotor.

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Optimization is the act of obtaining the best result under given circumstances. In design of any engineering system objective is to either minimize the effort or maximize the desired benefit, since the effort required or the benefit desired in any practical situation can be expressed as a function of certain decision variables. There are several attempts on the optimization of open-cycle regenerator gas-turbine power plant, fuel usage etc.. but very few works on optimization of Principle dimensions of Radial flow gas turbine rotor., one of that is a way to optimize the parameters (i.e. operating conditions), related to compressor performance, and based on artificial neural network. It inverts the neural network to find the optimum parameter value under given conditions by using of artificial neural network inverse, ANNi [5] another one is by using Genetic Algorithms [6].

The optimization techniques stated are the most robust, since they can be used for real and discrete variables, in highly or weakly non-linear problem types, for global search or refinement, and also for the resolution of multi-objective problems. ACO's are fundamentally different than other optimization techniques. In this paper an attempt is made to solve the non-linear optimization problem for inward flow radial turbine described in the past literature using an Ant colony Algorithms for given inlet design speciation.

2. OPTIMUM CHOICE OF PRINCIPAL DIMENSIONS AND NUMBER OF BLADES

The choice of the principal dimensions of a turbine rotor for a given set of inlet design specifications, as shown in Table 1, can be found by solving equations (1) to (4). An analytical method is indeed difficult and can be very time consuming, especially if the complete procedure has to be repeated for different design cases.

$$\frac{d_2 N}{\sqrt{C_P T_1}} = \left[\frac{60\sqrt{2}}{\pi}\right]\left[\frac{u_2}{C_s}\right]\left[\sqrt{1-\left(\frac{P_s}{P_1}\right)^{\frac{(\gamma-1)}{\gamma}}}\right] \tag{1}$$

$$\cos\alpha_2 = \left(\frac{C_{w2}}{u_2}\right)\left(\frac{\pi}{60}\right)\left(\frac{d_2 N}{\sqrt{C_p T_i}}\right)\left[\sqrt{\frac{1+\frac{(\gamma-1)M_2{}^2}{2}}{(\gamma-1)M_2{}^2}}\right] \tag{2}$$

$$\left(\frac{b_2}{d_2}\right) = \frac{m\sqrt{C_pT_i}}{d_2^2P_i}\left[\frac{1}{\pi B_{f2}}\left(\frac{\sqrt{\gamma-1}}{\gamma}\right)\right]\left[\frac{\left(1+\left(\frac{\gamma-1}{2}\right)M_2^2\right)^{\frac{\gamma+1}{2(\gamma-1)}}}{M_2\sin\alpha_2}\right] \quad (3)$$

Where the blockage factor at the rotor inlet can be given by

$$B_{f2} = 1 - \frac{1}{\pi}\left[N_b\left(\frac{t_2}{d_2}\right)\right] \quad (4)$$

Where the blockage factor at the rotor inlet can be given by

$$\frac{m\sqrt{C_pT_i}}{d_2^2P_i} = \left(\frac{P_e}{P_i}\right)\left\{\left\{\frac{1}{\left[1-\eta_{tt}\left(1-(P_e/P_i)^{\frac{\gamma-1}{\gamma}}\right)\right]}\right\}^{\frac{1}{2}}\right\} \times \left\{B_{f2}\left(\frac{\pi}{4}\right)\left[\frac{\gamma}{\sqrt{\gamma-1}}\right]\left[\left(\frac{d_e{}^2}{d_2^2}\right) - \left(\frac{d_h^2}{d_2^2}\right)\right]\right\} \times \left\{\frac{M_{er}\sin\beta_e}{\left[1+\frac{\gamma-1}{2}(M_{er}\sin\beta_e{}^2)\right]^{\frac{\gamma+1}{2(\gamma+1)}}}\right\} \quad (5)$$

$$B_{f1} = \frac{2}{\pi} \times \frac{N_b\left(\frac{t_1}{d_2}\right)}{\pi\left[\left(\frac{d_e}{d_2}\right)+\left(\frac{d_h}{d_2}\right)\right]} \quad (6)$$

TABLE 1

INPUT DATA AT DESIGN POINT OF IFR TURBINE

Mass flow rate,	M=0.572 kg/s
Pressure ratio	p_i/p_e=3.6
Inlet stagnation temperature	T_i= 1000k
Rotational speed	N = 60,000rpm
Turbine efficiency	η_{tt}=0.87

3. PROBLEM FORMULATION

The frame size and weight of an IFR turbine is often an important parameter consideration, in view of this, the size of the turbine plays an important role in determining the overall size of such turbine. Therefore the aim is to minimize the rotor tip diameter *d2*, and this can be considered a constraint optimization problem. The procedure to solve such a problem is described as follows,

3.1 Selection of Main Principal Parameters of a Turbine Rotor.

The choices of selecting the principal dimensions (*Design Variables*) of a turbine rotor to solve this optimization problem are:

$$\begin{bmatrix} d_2 & = & X_1 \\ u_2/C_s & = & X_2 \\ \alpha_2 & = & X_3 \\ \psi_2 & = & X_4 \\ M_2 & = & X_5 \\ b_2/d_2 & = & X_6 \\ M_{er} & = & X_7 \\ \beta_e & = & X_8 \\ d_e/d_2 & = & X_9 \\ d_h/d_2 & = & X_{10} \end{bmatrix}$$

Where

d_2	=	Rotor tip diameter
u_2/c_s	=	Velocity ratio
α_2	=	Absolute flow angle at rotor inlet
ψ_2	= c_{w2}/u_2 =	Loading factor
M_2	=	Mach no. at rotor inlet
b_2/d_2	=	Width to tip diameter ratio
M_{er}	=	Mach no. at exducer tip diameter
β_e	=	Relative flow angle at exducer tip diameter
d_e/d_2	=	Exducer to rotor tip diameter ratio, and
d_h/d_2	=	Hub to tip diameter ratio.

3.2 Formulation of the Objective Function

The main objective of problem is to minimize the rotor tip diameter and it can be stated as Minimize rotor tip diameter,

$$f(x) = d_2 \quad (7)$$

3.3 Formulation of equality and un equality constraints

The following equality and inequality constraints were obtained by substituting the input data given in the table 1

3.3.1. Equality Constraints

$$g_1 = 56x_1 - 14x_2 \quad (8)$$

$$g_2 = \cos x_3 - 2.93215\, x_4 x_1 \sqrt{\frac{1+0.6161\, x_5^2}{0.3232\, x_5^2}} \quad (9)$$

$$g_3 = x_6 - \frac{0.000235}{x_1^2}\left[\frac{x_1-0.08N_b}{x_1}\right]\left[\frac{\left((1+0.16161x_5^2)^{3.5}\right)}{x_5\sin x_3}\right] \quad (10)$$

$$g_4 = \frac{0.0017}{x_1^2} - 0.58\left[1-\frac{0.08N_b}{x_1}\right]\left[\frac{x_7(x_9^2-x_{10}^2)\sin x_8}{(1+0.16161x_7\sin^2 x_8)^{3.5}}\right] \quad (11)$$

3.3.2 Inequality Constraints

$$g_5 = x_1 - 0.2 \le 0 \quad (12)$$
$$g_6 = x_2 - 0.707 \le 0 \quad (13)$$
$$g_7 = x_3 - 21 \le 0 \quad (14)$$
$$g_8 = x_4 - 1 \le 0 \quad (15)$$
$$g_9 = x_5 - 1 \le 0 \quad (16)$$
$$g_{10} = x_6 - 0.15 \le 0 \quad (17)$$
$$g_{11} = x_7 - 1 \le 0 \quad (18)$$
$$g_{12} = 25 - x_8 \le 0 \quad (19)$$
$$g_{13} = x_9 - 0.75 \le 0 \quad (20)$$
$$g_{14} = 0.25 - x_{10} \le 0 \quad (21)$$

A computer C++ program has been developed for an Ant Colony algorithm to solve this non-linear optimization problem.

4. THE ANT COLONY OPTIMIZATION APPROACH

In the ant colony optimization (ACO) meta-heuristic a colony of artificial ants cooperates in finding good solutions to difficult discrete optimization problems. Cooperation is a key design component of ACO algorithms: The choice is to allocate the computational resources to a set of relatively simple agents (artificial ants) that communicate indirectly by

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stigmergy. Good solutions are an emergent property of the agents' cooperative interaction.

Artificial ants have a double nature. On the one hand, they are an abstraction of those behavioral traits of real ants which seemed to be at the heart of the shortest path finding behavior observed in real ant colonies. On the other hand, they have been enriched with some capabilities which do not find a natural counterpart. In fact, we want ant colony optimization to be an engineering approach to the design and implementation of software systems for the solution of difficult optimization problems. It is therefore reasonable to give artificial ants some capabilities that, although not corresponding to any capacity of their real ant's counterparts, make them more effective and efficient. In the following we discuss first the nature inspired characteristics of artificial ants, and then how they differ from real ants.

4.1 Similarities and differences with real ants

Most of the ideas of ACO stem from real ants. In particular, the use of: (i) a colony of cooperating individuals, (ii) an (artificial) pheromone trail for local stigmergetic communication, (iii) a sequence of local moves to find shortest paths, and (iv) a stochastic decision policy using local information and no look ahead.

4.1.1 Colony of cooperating individuals:

As real ant colonies, ant algorithms are composed of a population, or colony, of concurrent and asynchronous entities globally cooperating to find a good "solution" to the task under consideration. Although the complexity of each artificial ant is such that it can build a feasible solution (as a real ant can find somehow a path between the nest and the food), high quality solutions are the result of the cooperation among the individuals of the whole colony. Ants cooperate by means of the information they concurrently read/write on the problem's states they visit, as explained in the next item.

4.1.2 Pheromone trail and stigmergy:

Artificial ants modify some aspects of their environment as the real ants do. While real ants deposit on the world's state they visit a chemical substance, the pheromone, artificial ants change some numeric information locally stored in the problem's state they visit. This information takes into account the ant's current history/performance and can be read/written by any ant accessing the state. By analogy, we call this numeric information artificial pheromone trail, pheromone trail for short in the following. In ACO algorithms local pheromone trails are the only communication channels among the ants. This stigmergetic form of communication plays a major role in the utilization of collective knowledge. Its main effect is to change the way the environment (the problem landscape) is locally perceived by the ants as a function of all the past history of the whole ant colony. Usually, in ACO algorithms an evaporation mechanism, similar to real pheromone evaporation, modifies pheromone information over time. Pheromone evaporation allows the ant colony to slowly forget its past history so that it can direct its search towards new directions without being over-constrained by past decisions.

4.1.3 Shortest path searching and local moves:

Artificial and real ants share a common task: to find a shortest (minimum cost) path joining an origin (nest) to destination (food) sites. Real ants do not jump, they just walk through adjacent terrain's states, and so do artificial ants, moving step-by-step through "adjacent states" of the problem. Of course, exact definitions of state and adjacency are problem-specific.

4.1.4 Stochastic and myopic state transition policy:

Artificial ants, as real ones, build solutions applying a probabilistic decision policy to move through adjacent states. As for real ants, the artificial ants' policy makes use of local information only and it does not make use of lookahead to predict future states. Therefore, the applied policy is completely local, in space and time. The policy is a function of both the a priori information represented by the problem specifications (equivalent to the terrain's structure for real ants), and of the local modifications in the environment (pheromone trails) induced by past ants.

5. RESULTS AND DISCUSSION

The computer program written in C was run for different number of blades ranging from 12 to 20, in accordance with the assumed efficiency. The final out put results for each run give the numerical values of the matrix X.

Table 2 gives optimum values of design variables obtained after running the program for ACO Algorithm for different number of blades. As one would expect the tip width increases over the blade range because increasing the number of blades will reduce the flow passage area. To keep the mass flow rate the same the blade width must increase

TABLE 2

OPTIMUM VALUES OF THE DESIGN VARIABLES FOR DIFFERENT NO. OF BLADES ON OPTIMIZATION

	12	13	14	15	16	17	18	19	20
X_1	16.8	16.9	17	17	17	17	17	17	17
X_2	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
X_3	19	18.5	19	18	18	18	18	19	19
X_4	0.7	0.7	0.9	0.9	0.9	0.9	0.9	0.8	0.8
X_5	0.9	0.7	0.7	0.7	0.7	0.7	0.7	0.8	0.8
X_6	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
X_7	0.9	0.7	0.8	0.8	0.8	0.8	0.8	0.9	0.9
X_8	25	25	25	25	25	25	25	25	25
X_9	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
X_{10}	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3

TABLE 3

DESIGN DATA OUTPUT FOR TURBINE ROTOR

Design parameter	Design values
N_b	12
d_2	16.824
b_2	0.8984
d_e	10.96
d_h	402547
α_2	19 degrees
β_e	25 degrees

After comparing the values with ACO algorithm the ant colony optimization values are minimized and got the best results by giving 100 iterations and the best value for number of blades is hence occurred at 12 blades. The results obtained by the C++ programme are shown in Table 3

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A graph has been plotted with these 100 iteration values by taking No of iterations on X axis and Function values on Y-axis. As shown in fig 1. The Local minima and global minima values are clearly identified pointed out clearly. Hence From the graph also it is clear that ACO is coming out of the Local Minima to global minima values.

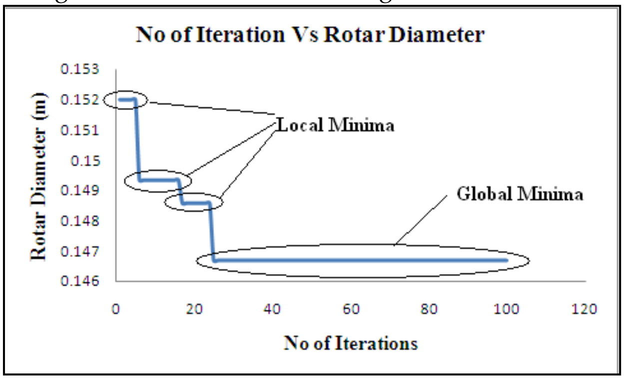

Figure 1 Variation of objective function with No of iterations

Results that were obtained for the different blade numbers from 13 to 20 like as blade number 12 discussed above and they are given in from the table 4 to 6. These results compared with the previous work carried out by GA [6]. It is found that for each Blade number, ACO gives the best results than that of GA results.

TABLE 4

COMPARISON BETWEEN GA [6] AND ACO FROM BLADE NO 12 TO 14

	12		13		14	
	GA	ACO	GA	ACO	GA	ACO
X_1	16.8	0.14	16.9	0.14	17	0.14
X_2	0.7	0.58	0.7	0.58	0.7	0.61
X_3	19	5.32	18.5	0.84	19	5.88
X_4	0.7	0.9	0.7	0.57	0.9	0.37
X_5	0.9	0.68	0.7	0.92	0.7	0.65
X_6	0.1	0.52	0.1	0.13	0.1	0.02
X_7	0.9	0.88	0.7	0.82	0.8	0.68
X_8	25	48	25	80	25	74
X_9	0.7	0.1	0.7	0.07	0.7	0.04
X_{10}	0.3	0.95	0.3	0.97	0.3	0.98

TABLE 5

COMPARISON BETWEEN GA [6] AND ACO FROM BLADE NO 15 TO 17

	15		16		17	
	GA	ACO	GA	ACO	GA	ACO
`X_1	17	0.14	17	0.15	17	0.15
X_2	0.7	0.59	0.7	0.63	0.7	0.64
X_3	18	19.8	18	10.9	18	11.1
X_4	0.9	0.21	0.9	0.30	0.9	0.57
X_5	0.7	0.56	0.7	0.58	0.7	0.57
X_6	0.1	0.11	0.1	0.08	0.1	0.06
X_7	0.8	0.81	0.8	0.06	0.8	0.69
X_8	25	30	25	36	25	100
X_9	0.7	0.01	0.7	0.2	0.7	0.48
X_{10}	0.3	1	0.3	0.99	0.3	1

TABLE 6

COMPARISON BETWEEN GA [6]AND ACO FROM BLADE NO 18 TO 20

	18		19		20	
	GA	ACO	G A	ACO	GA	ACO
X_1	17	0.15	17	0.15	17	0.15
X_2	0.7	0.65	0.7	0.64	0.7	0.63
X_3	18	19.8	19	13.4	19	5.88
X_4	0.9	0.37	0.8	0.13	0.8	0.50
X_5	0.7	0.6	0.8	0.67	0.8	0.6
X_6	0.1	1.10	0.1	0.12	0.1	0.07
X_7	0.8	0.68	0.9	0.14	0.9	0.78
X_8	25	49	25	61	61	27
X_9	0.7	0.54	0.7	0.14	0.7	0.13
X_{10}	0.3	0.91	0.3	0.6	0.3	1

6. CONCLUSIONS

In paper a new multi criterion design optimization method based on swam intelligence algorithms are presented. The main aim of these methods are to reduce the computing time while running an evolutionary algorithm program and to facilitate the decision making process with multi objectives. This means that the methods make the process of seeking the preferred solution more effective considering both the computation time and the decision-making problem. Our study presents two novel and interesting methods for finding the optimum robot gripper configuration with Single objective functions. From results and discussions, this paper concludes that the proposed Ant Colony Optimization is superior in terms of optimum value than GA. It is found that 13% improvement in the optimum value from ACO than GA. 13 percent decrease of Rotor diameter leads to decrease in Design and Manufacturing cost.

NOMENCLATURE

A = Area of flow at stations.
A_N = Area of nozzle.
A_R = Area of rotor blade section.
A_{root} = Area of cross-section of blade at root.
B = Blade width in mm or cm.
B_r = Blockage factor.
C = Absolute flow velocity in m/sec.
C_p = Specific heat capacity at constant pressure kj/kg k.
D = Diameter in cm or mm.
m = Mass flow rate kg/s.
M = Absolute Mach number.
M_r = Relative Mach number.
N = Rotational speed, rpm.
N_b = Number of blades.
R_e = Reynolds number.
t = Blade thickness.

T	=	Stagnation temperature.
U	=	Rotor tip velocity m/sec.
α	=	Absolute flow angle relative to axial direction.
β	=	Relative flow angle relative to axial direction.
γ	=	Ratio of specific heats.
ή	=	Efficiency.
ώ	=	Angular velocity, rad/sec.

Subscripts:

0	**-**	Stagnation condition.
1	-	Rotor outlet station at mean.
2	-	Rotor inlet station.
3	-	Exit condition, exducer.

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