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Sizing and Geometry Optimization of Pin Connected Structures Via Real Coded Genetic Algorithm (RCGA)

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SIZING AND GEOMETRY OPTIMIZATION OF PIN CONNECTED STRUCTURES VIA REAL CODED GENETIC ALGORITHM RCGA

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Abstract- Optimization of sizing and geometry is one of the active areas of research in structural engineering. In sizing optimization of structures the goal is minimizing the weight of the structure while the cross sectional areas of the members are considered as design variables. In this kind of optimization the nodal coordinates and connectivity among different members are considered stable. In the geometry optimization the nodal coordinates are considered as design variables. Simultaneous sizing and geometry optimization are considered in most structural optimization problems. In this article, Real Coded Genetic Algorithm (RCGA) is utilized to optimize sizing and geometry of pin connected structures. Also some schemes and a kind of mutation which is called class mutation are used to increase the efficiency of RCGA (optimum RCGA). In class mutation contrary to multiple mutation, design variables with the same characteristics are classified into one group so there is more handle on the variables during the mutation process. The performance characteristics of above method are investigated by two pin connected structures (18 and 25 bar pin connected structures). Examples show that the proposed method gives better results than some other schemes such as numerical methods and the classical GA.

Index Terms - sizing and geometry optimization, optimum Real Coded Genetic Algorithm, Class Mutation, pin connected structures.

I. Introduction

Optimization of sizing and geometry is one of the active areas of research in structural engineering. In sizing optimization of structures the goal is minimizing the weight of the structure while the cross sectional areas of the members are considered as design variables. In this kind of optimization the nodal coordinates and connectivity among different members are considered stable. In the geometry optimization the nodal coordinates are considered as design variables. Simultaneous sizing and geometry optimization are considered in most structural optimization problems.

Structural optimization is based on two methods: Numerical methods and Evolutionary techniques. Numerical methods have been developed earlier than Evolutionary techniques which have been used by different researchers e.g., Vanderplaats and Moses [1] separated the design space into two parts and used different methods for optimization in each subspace: a fully stressed design was applied for optimization in sizing subspace, and steepest descent method was used for optimization in geometry subspace. Imai and Schmit [2] have used an advanced primal-dual method, called the multiplier method. Pederson [3] has used The SLP (sequence of linear programs) method with move limits in sizing and geometry optimization. Lipson and Gwin [4] applied the complex method to optimize the size and shape of trusses.

Genetic Algorithm (GA) is one of the evolutionary algorithms that can be used for solving the structural optimization problems [5]. GA was introduced by John Holland in 1975 and developed by one of his students, Goldberg (1989). The advantage of this method to numerical methods is its ability to find the global minimum or maximum with continuous or discrete variables without using the derivatives of cost function [6]. Genetic algorithm is used directly only for solving unconstrained optimization problems so for solving constrained problems we should transform them to unconstrained problems by penalty function method [5]. This method also has been used by different researchers e.g: Soh and Yang [7], have used fuzzy logic for handling the GA operators in size and shape optimization of structures. Kaveh and Kalatjari [8], have used force method and genetic algorithm for sizing, and geometry optimization of trusses. Zheng, Querin and Barton [9] have used genetic programming method for sizing and geometry optimization in discrete structures. Ali, Behdinan and Fawaz [10] have investigated the applicability and viability of integration a FEM software package with binary GA. Hwang and He [11] have proposed a hybrid optimization algorithm which combines genetic algorithm and simulated annealing

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algorithm. Yang and Soh [12] have proposed a new GA-based evolution approach with the tournament selection scheme.

In the present paper an optimum RCGA, with a kind of new mutation operator called class mutation is used for solving the sizing and geometry optimization of structures.Two pin connected structures with continuous sizing and geometry variables are presented to demonstrate the robustness of the method.

II. Genetic Algorithm (GA)

GA is one of the methods which may be used to solve an optimization problem. This algorithm is based on natural selection using random numbers and does not require a good initial estimate [13].

a) *Binary Genetic Algorithm*

GA in the binary form works with binary string. Each string which is called chromosome is the member of population and the GA's operators that are inspired from the natural selection guide the population to the evolution or in other words, maximize the fitness function. A simple genetic algorithm consists of three operators: Reproduction, Crossover and Mutation.

Reproduction: The reproduction operator copies each chromosome proportional to its fitness function in the mating pool so the chromosome with the best fitness function will be copied more than the rest in the new population.

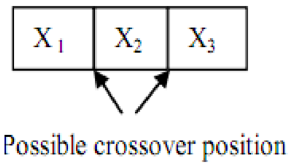
Crossover: The crossover operator works on two chromosomes and produces two new offspring that will inherit some characteristics of their parents. In this process two chromosomes in the mating pool are selected in pairs with (p_c) probability, then another random number determines the crossover point on the chromosome. Finally all bits of these two strings are exchanged between each other. Crossover point can be selected more than once on the chromosome.

Mutation: The mutation operator causes random changes in the people of population. In the process the chromosomes with probability of (p_m) are selected for mutation from the population, then a random number determines the position of mutation point and the bit in this place is complemented (Multiple Mutation) [14]-[15].

b) *Real Coded Genetic Algorithm (RCGA)*

Since in structural optimization problems with continuous variables we need to work on real numbers, we have used RCGA. In RCGA contrary to the binary method it is not required to decode the variables also, less processing memory is used [6]. In this method each chromosome is defined as an array of real numbers with the mutation and crossover operators working as shown in Fig. 1. The mutation can change the value of a real number randomly and the crossover can take place at the boundary of two real numbers [16].

$$\overline{X} = (x_1, x_2, x_3)$$



$$x_i \xrightarrow{\text{Mutation}} x_i = x_i + \text{rand}\left(-\frac{X_{imax}}{2}, \frac{X_{imax}}{2}\right)$$

X_{imax} is the maximum possible value for X_i

Fig. 1- Operation of mutation and crossover operators in RCGA

III. Penalty Function

Since GA is used only for solving unconstrained optimization problems, it is necessary to transform the constrained problem to the unconstrained optimization problem. In this article a quadratic penalty function is used as (1) [5]:

$$\min \varphi(A) = \frac{1}{L_f}\sum_1^N \rho_i l_i A_i + \beta\{\sum_1^N |(\frac{|\sigma_i|}{|\sigma_i^a|} - 1)^+|^2 + \sum_1^M |(\frac{|\delta_i|}{|\delta_i^a|} - 1)^+|^2\}$$

$$(\frac{|\sigma_i|}{|\sigma_i^a|} - 1)^+ = \max(\frac{|\sigma_i|}{|\sigma_i^a|} - 1, 0) \qquad (1)$$

$$(\frac{|\delta_i|}{|\delta_i^a|} - 1)^+ = \max(\frac{|\delta_i|}{|\delta_i^a|} - 1, 0)$$

$\sigma_i^a = \sigma_i^L$ when $\sigma i < 0$

$\sigma_i^a = \sigma_i^U$ when $\sigma i \geq 0$

$\delta_i^a = \delta_i^L$ when $\delta_i < 0$

$\delta_i^a = \delta_i^U$ when $\delta_i \geq 0$

where the last term is the penalty function, L_f is the normalizing factor, β is the penalty coefficient, M is the number of degrees of freedom, σ_i is stress in member i , δ_i is the displacement in the direction of degree of freedom i and σ_i^a and δ_i^a are allowable stres--ses and displacements, respectively.

IV. Methods for Increasing the Speed of RCGA (Optimum RCGA)

Typically in structural optimization problems with GAs, a population (pop) of many individuals with a high crossover rate (p_c) and very low mutation rate (p_m) is used [6]-[14]. Following the typical condition, RCGA with pop = 40, p_c = 0.7, p_m = 0.01 was tested for two sample space structures:

a) *Sample structures*

The samples contain 18 and 25 bar truss with sizing and geometry variables. Displacement method is used for analyzing the structure. The value of β (penalty coefficient) is increased by constant 10 in each 10 iteration and a value of 1000 is used for normalizing factor L_f.

i. *The 18 bar planar truss*

This classic, statically determined cantilever plane truss has been studied by different researchers [12]-[19]. The dimensions of the 18 bar truss are given in Fig.2. The modulus of elasticity is 6.895E4 Mpa and the density is 0.0272 N/cm³. The single loading condition is a set of vertical loads acting on the upper joints of the structure. The lower joints 3, 5, 7 and 9 are allowed to move in any direction in the x-y plane. Thus the locations of these joints are geometry variables. All the members of the structure have been categorized into four groups, as shown follow:

(1) $A_1=A_4=A_8=A_{12}=A_{16}$, (2) $A_2=A_6=A_{10}=A_{14}=A_{18}$,
(3) $A_3=A_7=A_{11}=A_{15}$, (4) $A_5=A_9=A_{13}=A_{17}$

So there are eight design variables: four geometry and four sizing variables. The sizing limit on the sizing variable is between 22.58 cm² and 116.128 cm² . Stress and Euler buckling constraint are imposed with an allowable stress of 137.9 Mpa and critical Euler buckling stress. The critical buckling stress of each member is determined by $4EA_i/(L_i^2)$ (L_i is the length of the ith member). The single loading condition is a set of vertical loads (P = - 89.96 kN) acting on the upper joints of the truss.

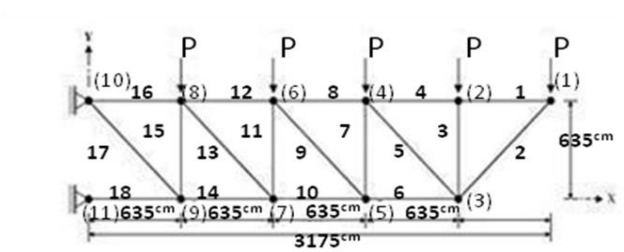


Fig. 2- 18 bar planar truss structure

ii. *The 25 bar space truss*

The 25 bar transmission tower that is shown in Fig. 3 has been optimized by different researchers [9]-[12]. In this example the material density is 0.0272 N/cm³ and the modulus of elasticity is 6.895E4 Mpa. The structure is subjected to two loading conditions that are shown in Table 1. There are 25 members that are divided into 8 groups:

(1)A_1 , (2)A_2~A_5 , (3)A_6~A_9 , (4)A_{10}~A_{11} , (5)A_{12}~A_{13} , (6)A_{14}~A_{17} , (7)A_{18}~A_{21} , (8)A_{22}~A_{25}.

The truss is required to remain symmetric with respect to both X-Z plane and the Y-Z plane. The coordinates of joints 1 and 2 were held constant, and joints 7-10 were required to lie in the X-Y plane. Due to the symmetry of the structure, there are a total of 13 design variables, which include eight sizing variables and five independent coordinates variables (X_4, Y_4, Z_4, X_8 and Y_8) for each load case. Stress and Euler buckling constraint are imposed with an allowable stress of 275.8 Mpa and critical Euler buckling stress. The critical buckling stress of each member is determined by $100.01\pi EA_i/(8L_i^2)$. The sizing limit on the sizing variable is between 0.0645 cm² and 6.451cm².

Table 1 Loading Conditions For 25 Bar Space Truss

Node	Case1(kN)			Case2(kN)		
	p_x	p_y	p_z	p_x	p_y	p_z
1	0.0	88.9	- 22.23	4.44	44.45	-22.22
2	0.0	-88.9	-22.23	0.0	44.45	-22.22
3	0.0	0.0	0.0	2.22	0.0	0.0
6	0.0	0.0	0.0	2.22	0.0	0.0

From the results the speed of convergence was not desirable. For achieving more speeds, a variety of sets of conditions with 40<pop<100, 0.6<p_c<0.9 and 0.001<p_m<0.1 were used. Although in all these cases convergence occurred and the parameters were obtained with enough accuracy, we did not have desirable increase in speed of the algorithm and the number of iteration remained around 9000 times.

For increasing the speed of convergence in the algorithm following observations were made [13]:

1- Increasing P_m .
2- Decreasing p_c (An increase in p_c causes the uniformity of the population, and the algorithm loses its efficiency).
3- Decreasing the population (Although the increase in pop decrease the number of iterations, the computation time per iteration increases and this altogether decreases the speed of the algorithm).

Regarding these facts the following conditions are used:
pop=6
p_c=0.25
p_m=0.75

After each iteration, the weakest individual in the new generation is replaced by the strongest in the old generation.

A new mutation operator, called class mutation, was used. After performing the above modifications, the number of iteration is reduced from 9000 to 2000 and the number of structural analysis is reduced from

360000 to 12000 times. In fact the speed of convergence is increased about 30 times. Since the last two steps have an important effect in speed up, they are explained in the following paragraph.

b) *Placing the strongest of old generation*

Since the process is highly randomized, to preserve the characteristics of the old generation, or in other words, to prevent the extinction of the old generation, after each iteration and the execution of the crossover and mutation operators the strongest individual from the previous population replaces the weakest one in new generation [13].

c) *Class mutation operator*

The results obtained with multiple mutation was not desirable Fig.4, perhaps due to the over-randomizing the process and the fact that in optimizing sizing and geometry, simultaneously a large number of design variables are encountered consisting of cross sectional areas and nodal coordinates which result in a design space with large dimensionality. So the class mutation with the following definition was used:

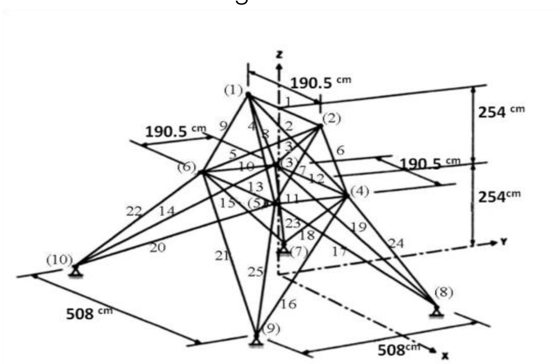


Fig. 3- 25 bar space truss structure

For class mutation the parameters with close physical concepts were classified into groups [13]. For example in 25 bar truss we have our groups as follows:

$A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8$

X_4, X_8

Y_4, Y_8

Z_4

The class mutation operator selects each class with the rate p_m (in this article 0.75), then randomly selects a member of the class and changes its value randomly. The comparison of the results for class mutation and multiple mutation is given in fig.4. Tables 2 and 3 compare the results obtained with the present method and other references for 18 and 25 bar trusses respectively. The optimized geometries for 18 and 25 bar trusses are given in Figs. 5 and 6.

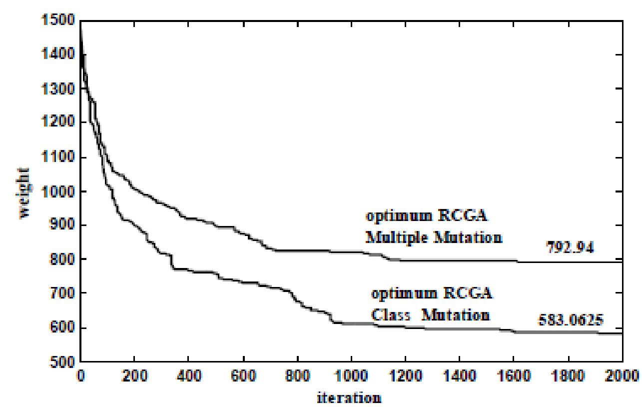


Fig. 4- Comparison of RCGA with multiple mutation and RCGA with class mutation in 25 bar truss

Table 2 Comparison of Design Variables For 18 Bar Plane Truss

Design variables	Imai[2]	Felix[17]	Yang[18]	Soh[12]	Rajeev[19]	Present Work
A_1 (cm^2)	72.51	73.16	81.35	81.22	80.64	74.8237
A_2 (cm^2)	101.16	124.38	116.77	115.54	104.83	113.9946
A_3 (cm^2)	51.16	70.77	35.29	35.48	51.61	33.4392
A_4 (cm^2)	41.87	34.19	22.83	22.90	25.80	33.8721
X_3 (cm)	2263.3	2526.2	2322.8	2310.8	2265.4	2322.0786
Y_3 (cm)	364.7	412.2	464.8	468.6	369.0	470.7841
X_5 (cm)	1544.8	1898.3	1643.3	1626.3	1550.9	1642.3716
Y_5 (cm)	267.7	261.3	374.3	375.4	300.2	370.5560
X_7 (cm)	969.5	1226.5	1052.0	1041.4	978.9	1055.9971
Y_7 (cm)	145.03	83.82	255.0	246.3	184.1	230.0145
X_9 (cm)	459.7	563.1	508	510.2	468.3	515.9065
Y_9 (cm)	-8.12	43.43	81.02	81.28	59.43	36.0527
Weight(N)	**20772.1**	**25422.8**	**20259.9**	**20166.9**	**20544.7**	**20164.28**

Table 3 Comparison of Design Variables For 25 Bar Space Truss

Design variables	Vanderplaats[1]	Yang[18]	Soh [7]	Yang [12]	Zheng[9]	Present Work
$A_1(cm^2)$	0.206	-	-	-	0.51	0.2219
$A_2(cm^2)$	3.638	-	-	-	4.96	2.5864
$A_3(cm^2)$	5.232	-	-	-	4.38	5.6774
$A_4(cm^2)$	0.180	-	-	-	0.51	0.2922
$A_5(cm^2)$	0.303	-	-	-	0.06	0.5516
$A_6(cm^2)$	0.625	-	-	-	0.06	0.9277
$A_7(cm^2)$	4.832	-	-	-	3.09	4.7974
$A_8(cm^2)$	3.554	-	-	-	3.09	3.7941
X_4(cm)	32.76	57.48	55.82	57.09	31.97	49.4593
Y_4(cm)	121.99	106.65	110.66	124.23	221.99	120.1051
Z_4(cm)	246.98	251.05	245.97	255.49	254	248.7924
X_8(cm)	93.98	39.57	35.89	64.03	158.97	44.2605
Y_8(cm)	238.98	209.21	206.09	249.25	254	233.2187
Weight(N)	**594.0**	**610.5**	**588.7**	**584.2**	**583.8**	**583.0625**

* - These values are not available

V. Conclusion

This article presents a new Real Coded Genetic Algorithm search which is called optimum RCGA with the class mutation operator for optimization of sizing and geometry of pin connected structures. The combination of modified optimum RCGA with displacement method was used for configuration optimization of structures. The method was examined for two sample pin connected structures (18 and 25 bar structures). The results proved that the modified optimum RCGA is able to find better solutions in comparison with other methods.

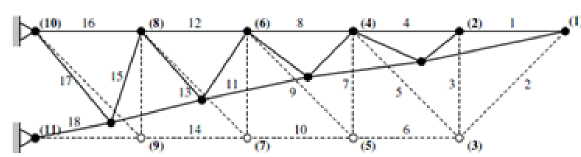


Fig. 5- 18 bar planar truss structure: initial structure and optimal structure

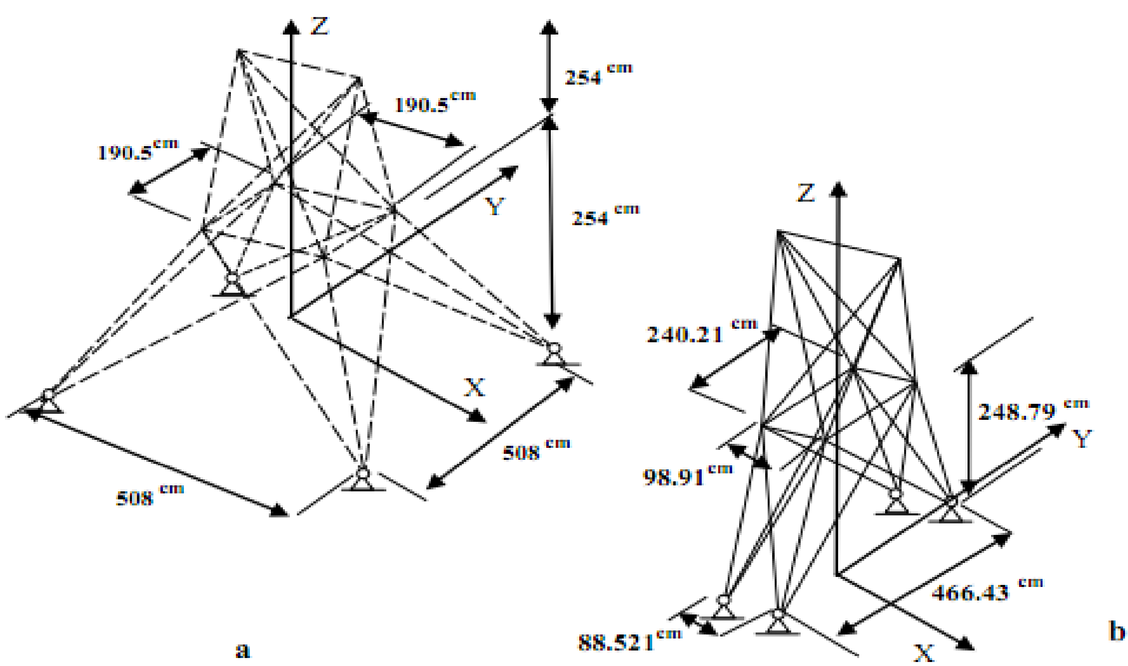


Fig. 6 25 bar truss: a initial structure, b optimal structure

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