Section Optimization Design of Discrete Structure with Improved Genetic Algorithms

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Abstract—**The structural members are generally to be selected from available profiles list is most important practical considerations in the optimization of discrete structures. Genetic algorithms show certain advantages over other classical optimization procedures in structural optimization of discrete variables.** In order to overcoming the shortcoming of simple GA, **we introduce the idea of directed mutation and present an active evolution in this paper. A growing operator is added to the evolution course to improve the search efficiency. Directed mutation is applied to the optimal individuals in each generation to improve the search efficiency. Application and experience on plane and space truss structures are discussed. The results of comparative studies of this method against other optimization algorithms for a class of representative structural design problems are reported to show the efficiency of the former. It is observed that this method often finds the region of the search space containing the global optimum.**

Keywords—**genetic algorithm, discrete** *structures, growing, operator, section* **optimization**

I. INTRODUCTION

In this paper, we will improve the normal genetic algorithms and apply it in the section optimization design of discrete structure. There are many engineering structural optimization problems which design variable is discrete. For example, in the structural optimization of electric power tower that the structural members are generally to be selected from available profiles which must be according to the national specifications. That the design variables are not continuous is the main characteristic of the discrete variables problems. This leads to the objective function and the constrained function are not continuous in the mathematical model. So many methods which are used in the continuous variables optimal problems can not be used to the discrete variables problems.

Genetic Algorithms(GAs) has been reported for optimum design of discrete structural systems. It shows certain advantages over other classical optimization procedures, e.g. it can successfully be applied to a broad range of diverse problem areas. GAs, which is applications of biological principles into computational algorithms, have been used to solve structural optimization problems. GAs is global search methods which have found application in wide areas, including optimum structural design. It applies the principles of survival of the fittest into the design of structures. It also has the ability to deal with discrete optimum design problems and do not require derivatives of functions, unlike classical optimization. In this article, a simple GAs[1] is used and improved by employing Directed Mutation instead of random mutation and adding a growing operator. Here, discrete optimal designs of bar structures including plane and space trusses are covered using a GAs based procedure. Then the implementation of the GAs program is discussed in detail with respect to discrete size optimization of trusses with applications. Two example problems are given and fully discussed.

In Section II we review GAs. Section III gives the discrete structural optimization problems. We improve the Simple GAs in Section IV. In Section V two classical examples are given to apply it. Section VI is a conclusion.

II. REVIEW OF GENETIC ALGORITHMS

GAs was founded in the mechanisms of biological evolution and natural genetics. It was originally proposed by J.H.Holland, which using genetic algorithms that mimic natural genetic processes in biological systems, to find high-quality solutions of many complex engineering problems [2]. This interest was followed by Kirkpatrick's simulated annealing technique [3] in 1983. Goldberg [4] has played an important role in the application of GAs to modern engineering. Various workers [5,6] have established the technique's validity for function optimization within civil and structural engineering applications. GAs is computationally simple, but powerful in the search for improved solutions.

GAs is a search technique based on mechanism of natural genetic and natural selection. The main procedure of the GAs is described as follows:

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1). Generation of initial population: Generate an initial population that consists of multiple individuals randomly generated (candidate solutions). Let the initial population be the current population.

2). Selection for reproduction: Choose pairs of individuals from the current population.

3). Generation of children: Apply a cross-over operator to the pairs of individuals chosen at step 2 to make children (new candidate solutions).

4). Selection for survival: Select individuals from the children generated at step 3 and the individuals in the current population to make the next population. Let next population be the current population.

5). Repeat the above steps from step 2 to step 4 until a certain stop condition is satisfied.

The process of designing a GAs consists two parts: (1) designing a representation and a cross-over operator, and (2) designing a generation-alternation model. In designing a representation and a cross-over operator, we determine how to represent a solution on the computer and how to generate a new solution from two or more solutions. The performance of GAs heavily depends on a representation and a crossover operator. It is important to consider characteristics of problem domain when designing a representation and a crossover operator.

GAs is global search method which has found application in many areas, including optimum structural design. Unfortunately the primary shortage of GAs is weak local convergence velocity. We introduce the idea of directed mutation into the normal GAs field and present an active evolution on the new research achievements in the genetics and biology evolutionism fields.

III. DISCRETE STRUCTURAL OPTIMIZATION PROBLEM

A. The optimal mathematics model

The optimum design problem of a discrete-sizing structural with displacement and load factor constraints can be written as follows:

Minize

$$G=W(X) \tag{1}$$

Satisfying

$$g_i(x)\le 0,\ i=1,2,3,\ \ldots\ldots m \tag{2}$$

$$X_{jmin}\le X_j\le X_{jmax}\quad j=1,2,3,\ldots\ldots n \tag{3}$$

where

$$X=[X_1,X_2,\ldots\ldots X_n]^T, \tag{4}$$

In Eqs.(1)-(4), $W(X)$ is the weight of the structure, $G=W(X)$ is the objective function, m and n represent, respectively, the number of constraints and independent design variables, X is the vector of design variables of dimension, g_i is the ith constraint on structural response and the inequalities in Eq.(3) are side constraints on the design variables. In discrete structural engineering optimization the vector X represents ready element sections which are to be chosen from an available list. Eqs. (1)-(4) represent a typical constrained optimization problem. The structural response constrains considered in this study include section stress, nodal displacements and buckling of elements.

B. Handling of constrains

GAs can only handle unconstrained problem. For GA use, the constrained problem is transformed into an unconstrained problem. The handling of constraints in GAs integrated structural optimization is an important issue in itself. GAs approach transforms the constrained structural design problem into an unconstrained problem through the use of penalty functions. A new (or modified) function is defined where the constraints that are violated, are penalized. Some of such approaches are studied in Michalewicz[7].

$$G_p(x)=W(x)+\sum_{j=1}^{m}W_j \tag{5}$$

where, , $W_j=r_j(g_j(x))^2, g_j=\begin{Bmatrix} g_j, g_j>0 \\ 0, g_j\le 0 \end{Bmatrix}$

In Eq.(5), g_j is the constraint function, which is zero in case of no violation, and is positive otherwise. And r_j is the penalty factor associated with the jth constraint of the problem.

C. Fitness function

The fitness of a population depends not only on the particular characteristics of its individuals but also on the profiles of all the other populations. GAs is usually used to maximize a problem's objective function. If an objective function is to be minimized it is necessary to transform it into a fitness function. There are many transformation methods available. The transform given by Eq.(6) was used by the author.

$$F=G_{max}-G_p \tag{6}$$

In Eqs(6), F is the fitness function value for the ith population string of the ith population generation. G_{max} is a value that larger than the largest G_p in the populations. Thus can ensure F is a value that larger than zero.

D. Termination criterion

On termination, two valuable pieces of information may be obtained; History-record and a predetermined number of feasible designs. The History-record file enables the user to view what happens during consecutive generations of the process through statistical treatment of the individuals. It contains information on the feasible best, average and worst design as the generation progress. Top-ten refers to the best ten different designs obtained during the optimization process until it is terminated. Each design for each element and the analysis results for the applied loading.

In this article, we adopt two termination criterions. One is the difference of the continuous optimal values small to the predetermined value. Another is the generation equal to the predetermined number of generations.

IV. IMPROVED GENETIC ALGORITHMS(IGA)

GAs is global search method which has found application in many areas, including optimum structural design. Unfortunately the primary shortage of GAs is weak local convergence velocity. We introduce the idea of directed mutation into the simple genetic algorithms field and present an active evolution on the new research achievements in the genetics and biology evolutionism fields. Directed mutation is applied to the optimal individuals in each generation to improve the search efficiency.

The research achievements of modern biology evolutionism fields indicate that the organism is not passivity and negative in the course of mutation. The mutation mechanism has an unrandomicity factor except of randomicity factor. The organism attach itself to the course of mutation and the evolution conform to the environment. We call this mutation is directed mutation. In this article, we add a growing operator to the directed mutation. The growing operation is defined to stress ratio of each design variables in the structure.

We define a new string Y= $[Y_1, Y_2, \ldots\ldots Y_n]^T$, where Y_i is named growing operator for each X_i in every generation. Y_i has only three values -1,0 and 1.The operation is executed as follows: If Y_i=1 ,the design variables must be increased; If Y_i=0 ,the design variables be unchanged; If Y_i=−1 ,the design variables must be decreased.

For example:

A is one design variable string, B is its growing operator string,

A: …0100 ┆ 1010 ┆ 0100…

B: …1 ┆ 0 ┆ -1…

The new string is C: …0101 ┆ 1010 ┆ 0011…

The integrated structural optimization flowchart is explained in Fig.1. The general characteristics of the program are:

1) Constraint violations are taken care of by penalty functions.

2) A structural analysis program is included in the main program to achieve a shorter computation time.

3) The program requires the preparation of the input file for both the structural analysis problem and the GAs required data.

4) For steel structures the program selects ready sections from particular profiles lists specified in the input data.

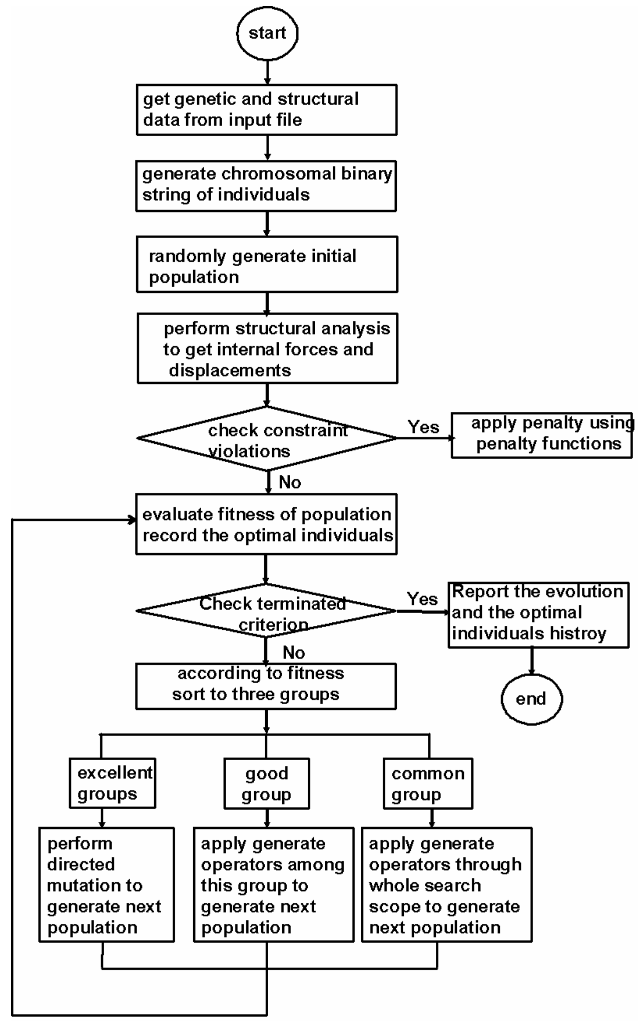

Figure.1. Improved Genetic Algorithms flowchart

V. USE OF IMPROVED GENETIC ALGORITHMS

The integrated structural optimization explained above is implemented as the program Improved Genetic Algorithms(IGA). The IGA program is conceived to handle the optimal design of structures. In its present form it handles size optimization of plane and space truss. For the operation of IGA, one has to prepare an input file where in addition to typical structural analysis input options, data related to genetic operations are also included. This are: population size, maximum number of generations, mutation probability, and crossover probability. Additionally, two more data are also considered. One is a penalty coefficient, which is needed in tackling constraint violations and the other one is to indicate the element group to which individual elements belong. The use of the program is facilitated by an interactive operation where the main components of the optimization procedure appear on the computer screen. The user chooses the input file starts the process.

A. A 12- bar plane truss

Let us consider a IGA problem of 12-bar plane truss and with a minimum weight as shown in Fig.2.

The design variables can be chosen from the profile list S={0.40，0.80，1,20，1.60，2.00，2.40，2.80，3.20，3.60，4.00，4.40，4.80，5.20，5.60，6.00，6.40，6.80，7.20，7.60，8.00，8.40，8.80，9.20，9.60，10.0，10.4，10.8，11.2，11.6，12.0，12.4，12.8}cm^2. Material properties: density of material is 7800kg/m^3, mogulus of elasticity is 206GPa, stress constraints:$[\sigma^+]=[\sigma^-]$=147.5MPa, load P_1=20kN, P_1=40kN, P_1=-30kN.

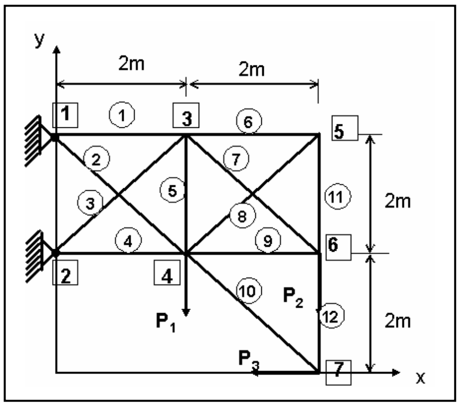

Figure.2. Twelve-bar plane truss structure

This optimization problem can be stated as follows:

$$minG=W(x)=\Sigma \rho_i l_i A_i \quad (7)$$

$X=(A_1, A_2, A_3, \ldots\ldots A_{12}), A_i \in S$

The size of population: pop-size=20, each design variables was denote by five binary number, the total design variables is 12, the length of string is 60, the maximum generation=120, the individual grouping probability=1:5:4.

TABLE I. TCOMPARISON TABLE FOR 10-BAR PLANE TRUSS

Method	Weight (kg)	1	2	3	4	5	6
Ref.[12]	127.6564	10.4	2.4	5.6	12.8	0.4	3.2
IGA	127.4205	10.4	1.2	6.0	12.6	0.4	2.4

Method	7	8	9	10	11	12
Ref.[12]	8.8	5.2	5.6	4.4	4.0	6.8
IGA	8.8	4.8	5.6	4.8	4.4	6.8

Table 1 shows the comparison of IGA and other methods [12]. It adopts 40 pop-size. The result indicates that the IGA optimization has the lightest weight and the fastest convergence velocity.

B. A 25- bar space truss

In order to showing the advantage of IGA's on discrete optimization, another example is calculated. This example chosen is the classical 25-bar space truss showed in Fig.3.

The design variables can be chosen from the profile list S={0.51613, 0.64516, 1.9355, 4.5161, 6.4516, 12.903, 19.355, 25.806}cm2. Material properties: density of material is 2770kg/m^3 , mogulus of elasticity is 68.9GPa, stress constraints:$[\sigma^+]=[\sigma^-]$=265.6MPa, displacement constraints can not larger than 8.89mm in *x* and *y* directions.

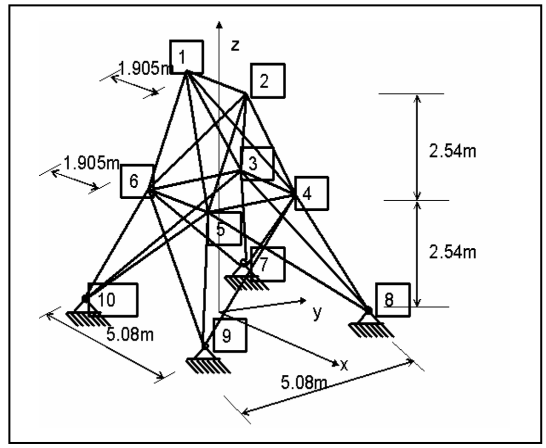

Figure.4. Twenty-five bar truss structure

The size of population: pop-size=20, each design variables was denote by three binary number, the total design variables is 8, the length of string is 24, the maximum generation=120, the individual group probability=2:4:4.

Table 4 shows the comparison of IGA and other methods. The objective function convergence to the optimal value after 80 generations and its value is 268.237kg . That result is smaller than Ref.[13].

TABLE II. LOADING DATA(kN)

Case number	joint number	P_x	P_y	P_z
1	1	4.4498	44,498	-22.249
	2	0	44.498	-22.249
	3	2.2249	0	0
	6	2.2249	0	0
2	1	0	88.996	-22.249
	2	0	-88.996	-22.249

TABLE III. MEMBER LINKING DETAIL FOR 25- BAR TRUSS

Group number	members
1	1-2
2	1-4，2-3，1-5，2-6
3	2-5，2-4，1-3，1-6
4	3-6，4-5
5	3-4，5-6
6	3-10，6-7，4-9，5-8
7	3-8，4-7，6-9，5-10
8	3-7，4-8，5-9，6-10

TABLE IV. THE COMPARISON TABLE FOR 25-BAR SPACE TRUSS

method	weight (kg)	Design variables		
		A_1	A_2	A_3
Ref.[13]	268．44	0.64516	12.903	19.355
IGA	268.237	0.51613	12.903	19.355

Design variables				
A_4	A_5	A_6	A_7	A_8
0.64516	0.51613	4.5161	12.903	19.355
0.51613	0.51613	4.5161	12.903	19.355

VI. CONCLUSIONS

This study has shown that the genetic algorithm is a useful technique in structural optimization. To overcome the shortage of the simple GAs, we introduce the idea of directed mutation into the simple genetic algorithm field and present an active evolution on the new research achievements in the genetics and biology evolutionism fields. We introduce the growing operator in the procedure. According to the fitness of generations , the population is sort to three groups: excellent group, good group and common group. Directed mutation is applied to the excellent group in each generation. A growing operator is added to the evolution course to improve the search efficiency. Niche perform is applied to the good group to improve the reliability of global convergence. General genetic perform is applied to the common group to ensure individuals diversity. This improvement is feasibility and effective through the example.

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