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Convergence and Calculation Speed of Genetic Algorithm in Structural Engineering Optimization

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Abstract
In view of the existing genetic algorithm in structural engineering optimization has poor convergence, computational speed is slow, a optimization scheme of genetic algorithm is proposed in this paper based on the crossover operator and fitness function. The first use of the hybrid mechanism of the single point crossover operator of genetic algorithm is improved, in order to improve the searching space, and then the small to adapt to the optimization of the habitat mechanism of sharing function convergence. The simulation results show that, the crossover operator and fitness function based genetic algorithm optimization in structural engineering optimization has better, faster and better stability.

Key words: STRUCTURAL ENGINEERING OPTIMIZATION, IMPROVED GENETIC ALGORITHM, CONVERGENCE OPTIMIZATION, FITNESS FUNCTION OPTIMIZATION.

1. Introduction

At any times, we need to design and construct the engineering structures. Era progress, the requirement for structure is higher, factors to consider in the design is more complex, and with the traditional design method, it is often difficult to deal with[1]. If you want to design the structure to conform to the ideal as far as possible, it would be more in need of new modern structural optimization theory and method. Structure design optimization can make the structure to achieve the requirement of the economic and security[2]. So the optimization design is the new development and achievements of structure design, it has important engineering significance and wide application prospects [3].

Structure optimization design has a history of hundred years since Maxwell's theory and Michelle's papers on the issue of minimum volume frame structure design appear, since Schmitt used mathematical programming to solve the structure optimization design also had a history of 45 years, especially in the past 35 years, structure optimization design in the aspects of theory, algorithms and applications have made great development[4]. American Scientist Dantzig proposed simplex method, this method is suitable for solving linear programming problem[5].Then Kamaka proposed interior-point method and ellipsoid algorithm(namely polynomial algorithm) [6]. For the nonlinear problem, people use linear theory to solve the nonlinear problem at the beginning, then based on the quadratic function, approximate to other nonlinear function, on the such basis, there are many classical optimization methods, such as unconstrained method includes: the conjugate gradient method, the steepest descent method (steepest), Newton's method (Newton algorithm), quasi-newton method (pseudo Newton algorithm), trust region method, etc. [7].The science and technology are in a multidisciplinary cross each other and complement each other and the rapid development of computer technology, the request for efficient optimization techniques and intelligent computing is higher, based on the mathematical optimization technology, by optimum identification, definition and modeling solving various kinds of optimization problems, it is widely used in many fields[8]. McCulloch and Pitts established artificial neural network model, and it was extended "perceptron" optimization models later, and then Hopfield applied neural network to the combinatorial optimization problems successfully, because of the artificial neural network has strong adaptability, learning ability and massive parallel computing ability, it has been widely applied to various kinds of practical engineering, such as control and optimization, predictive modeling, signal processing, communications, etc. [9].

In this paper, the genetic algorithm of structural engineering optimization is improved, optimize the crossover operator and fitness function, in order to improve its convergence and computation speed in the optimization of structural engineering.

2. Genetic Algorithm

GA algorithm is an iterative process based on fitness function, and through applying genetic operations to species individuals to realize the individual structure reorganization of the specie. In this process, the specie individual is optimized by generations and gradually approximate the optimal solution [10].

Genetic algorithm uses in fitness function to evaluate the individual strengths and weaknesses in operation, the design of fitness function has an important influence on the performance of genetic algorithm.

(1)The maximum optimization problem:

$$Fitness(f(x)) = -f(x) \qquad (1)$$

The minimum optimization problem:

$$Fitness(f(x)) = -f(x) \qquad (2)$$

The fitness function with a simple expression form in the real life application existed the following problems: most of the time it does not satisfy the nonnegative requirement of the roulette wheel selection; If some function value has large difference, it will lead to the population average fitness value cannot reflect the average performance of population, it will ultimately affect the effect of the algorithm.

(2) The biggest optimization problem:

$$Fitness(f(x)) = \begin{cases} f(x)+C_{\min}, & f(x)+C_{\min} > 0 \\ 0 & , f(x)+C_{\min} \le 0 \end{cases} \qquad (3)$$

$C_{\min}$ is a preestablish suitable small number, it is the smallest function value of the objective function since we have estimated.

The minimum optimization problem:

$$Fitness(f(x)) = \begin{cases} C_{\max} - f(x), & C_{\max} - f(x) > 0 \\ 0 & , C_{\max} - f(x) \le 0 \end{cases} \qquad (4)$$

$C_{\max}$ is a preestablish suitable big number, it is the biggest function value of the objective function since we have estimated.

Because $C_{\max}$, $C_{\max}$ is prior estimated, it is not precise enough, and it often makes the fitness function not sensitive enough to cause algorithm performance degradation.

(3) The biggest optimization problem:

$$Fitness(f(x)) = \frac{1}{1+c-f(x)}, c \geq 0, c-f(x) \geq 0 \quad (5)$$

The minimum optimization problem:

$$Fitness(f(x)) = \frac{1}{1+c+f(x)}, c \geq 0, c+f(x) \geq 0 \quad (6)$$

Among them, c is the prior estimated value, so it has the similar problem in (2).

The basic process and structure of the standard genetic algorithm is shown in figure 1.

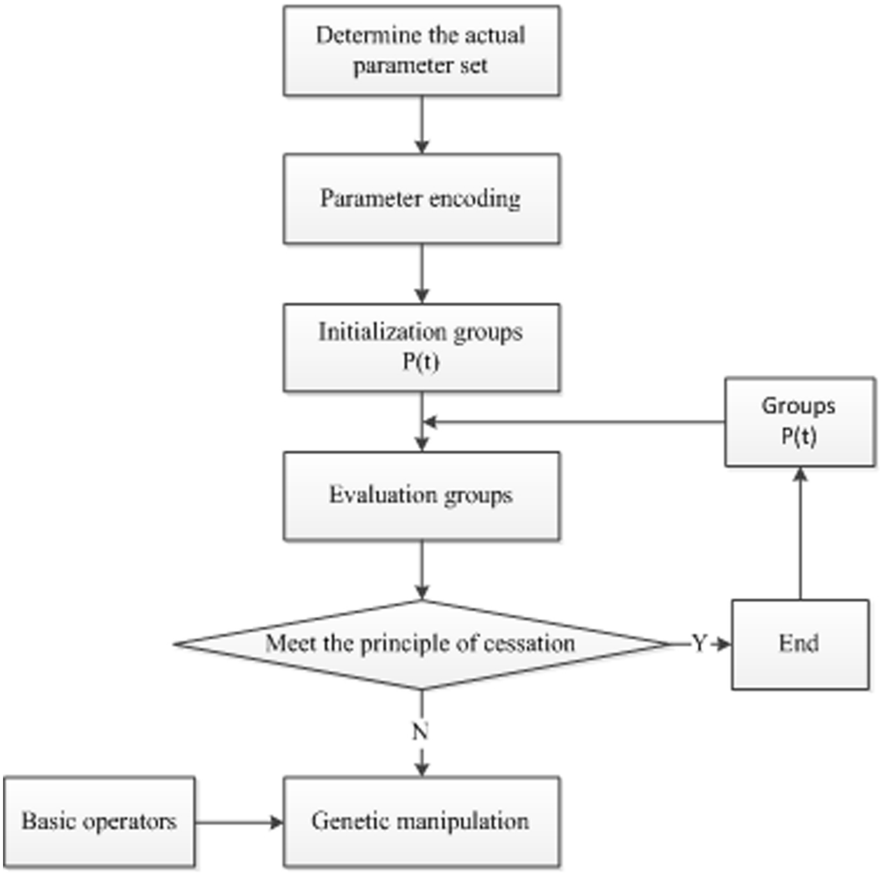

Figure1. The basic process of genetic algorithm

3. The Operator Optimization of Genetic Algorithm

3.1. Crossover Operator Optimization

Crossover operation is the main operation of genetic algorithm, only by constantly crossover operation to produce the new individual, so that we can get the excellent individuals. In order to increase the searching space of population, this paper proposed a crossover operator based on mixed single point.

Suppose when it evolutes to the t th generation, two male parent respectively are: $X_a^t = [x_{a,1}^t, \ldots, x_{a,k}^t, \ldots, x_{a,n}^t]$ and $X_b^t = [x_{b,1}^t, \ldots, x_{b,k}^t, \ldots, x_{b,n}^t]$, after crossover, we can get the $t+1$ th generation individuals are $X_b^{t+1} = [x_{b,1}^{t+1}, \ldots, x_{b,k}^{t+1}, \ldots, x_{b,n}^{t+1}]$ and $X_b^{t+1} = [x_{b,1}^{t+1}, \ldots, x_{b,k}^{t+1}, \ldots, x_{b,n}^{t+1}]$, Intersection are respectively $x_{a,k}^t$ and k . The cross way here is to calculate the k th genes of individual X_a^t and $x_{a,s}^{t+1}$ through type (7), two new genes $x_{a,s}^{t+1}$ and $k+1$ are produced, and put it back in place, and then exchange the $k+1$ th to X_b^t th genes of X_b^t and X_b^t, eventually it produces two new individuals, the calculation of the k th gene is as follows:

$$\begin{cases} x_{a,s}^{t+1} = \alpha x_{a,k}^t + (1-\alpha) x_{b,k}^t \\ x_{b,s}^{t+1} = (1-\alpha) x_{a,k}^t + \alpha x_{b,k}^t \end{cases} \quad (7)$$

Among them $\alpha = \frac{rank(X_a^t)}{rank(X_a^t) + rank(X_b^t)}$, $rank(X)$ is the column rank of individual α . Along with the growing of evolution algebra, α is more and more tend to be 0.5. In the t th generation, the main steps of mixed single point are as shown below.

(1) Choose two male parent from the population randomly, $p1^t = [x_{a,1}^t, \ldots, x_{a,k}^t, \ldots, x_{a,n}^t]$ and $p2^t = [x_{b,1}^t, \ldots, x_{b,k}^t, \ldots, x_{b,n}^t]$, and choose the kth of the variables in the two male parent, among them $k = round(rand \cdot (n-1) + 1)$, n is the number of decision variables;

(2) If $rand < p_c$, p_c is crossover probability, $\alpha = \frac{rank(p1)}{rank(p1) + rank(p2)}$, get into (3), or $rand > p_c$, get into (5);

(3) $\begin{cases} ch1^t(k) = \alpha x_{a,k}^t + (1-\alpha)x_{b,k}^t \\ ch2^t(k) = (1-\alpha)x_{a,k}^t + \alpha x_{b,k}^t \end{cases}$ is the transformation form of type (7);

(4) The new generation of two individuals are:

$$ch1^{t+1} = [p1^t(1:k-1), ch1^t(k), p2^t(k+1:n)] \quad (8)$$

$$ch2^{t+1} = [p2^t(1:k-1), ch2^t(k), p1^t(k+1:n)] \quad (9)$$

(5) Make the father individual which is chosen before as child individual, $ch1^{t+1} = p1^t$, $ch2^{t+1} = p2^t$.

Repeat the process until the number of new individual is equal to the number of populations that stop crossover operation.

3.2. The Fitness Function Sharing Optimization Based on Niche

Direct purpose of fitness sharing function is to separate the different peak of search space on geography, each peak accepts a certain percentage number of the individuals, the size of the ratio has relation with peak height. In order to realize the distribution, use sharing method to reduce the goal of individual fitness, namely the fitness value m_i is divided by a niche count m_i for sharing function, make niche count m_i as an individual adjacent set intensity estimates.

$$m_i = \sum_{j \in Pop} sh[d[i,j]] \quad (10)$$

Among the type above, $d[i,j]$ is the distance of j and j , $sh[0]=1$ is a sharing function, it is a decreasing function, $sh[0]=1$ and $sh[d \geq \sigma_{share}] = 0$.

The following is a typical triangle shared function:

$$sh(d) = \begin{cases} 1 - \dfrac{d}{\sigma_{share}}, d \leq \sigma_{share} \\ 0, d > \sigma_{share} \end{cases} \quad (11)$$

Here σ_{share} is the niche radius r , it is given by users themselves, it is the minimum distance between good peak individuals. The individual within the scope of distance σ_{share} to cut each other fitness. Because these individual niche size is the same, so they convergence in a niche, avoid the convergence of the entire population.When a niche is full, the niche count increases, it will make sharing function lower than other niche.

In order to define a niche, this paper adopts a method which combined hamming distance measure and fitness distance.If $d_1(x_i,x_j)$ is the hamming distance of any two individuals x_i and x_j , $d_2(x_i,x_j)$ is the fitness distance, then sharing function can be defined as:

$$Sh(x_i,x_j) = \begin{cases} 1 - \dfrac{d_1(x_i,x_j)}{\sigma_1}, d_1(x_i,x_j) < \sigma_1, d_2(x_i,x_j) \geq \sigma_2 \\ 1 - \dfrac{d_2(x_i,x_j)}{\sigma_2}, d_1(x_i,x_j) \geq \sigma_1, d_2(x_i,x_j) < \sigma_2 \\ 1 - \dfrac{d_1(x_i,x_j)d_2(x_i,x_j)}{\sigma_1\sigma_2}, d_1(x_i,x_j) < \sigma_1, d_2(x_i,x_j) < \sigma_2 \\ 0, else \end{cases} \quad (12)$$

Here σ_1 and σ_2 are the niche radius, namely it is the maximum individual distance of the genotype and phenotype respectively within a a niche.

Finally, the fitness function of the individual after sharing change into the form of the following:

$$f'(x_i) = \frac{f(x_i)}{\sum_{j=1}^{M} sh(x_i,x_j)} \quad (13)$$

Here $f(x_i)$ and $\sigma^+ = 20$ are the expressions of individual fitness function when it is before shared and after shared.

4. The Algorithm Simulation

In order to verify the effectiveness of the improved genetic algorithm proposed in this paper, the simulation experiment was done. In this paper, make 3 pole plane truss as example, modulus of elasticity is $E = 1.0E+6$ the allowable stress of each bar are $\sigma^+ = 20$, $\sigma^- = -15$. the lower limit of cross-sectional area is 0.645, up to 12.9, its structure is shown in Fig 2:

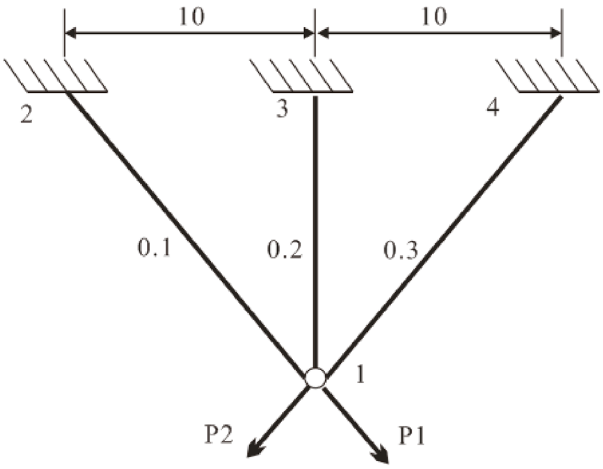

Figure 4. Overall optimization truss rod

Using the improved genetic algorithm (IGA) proposed in this paper, the structural optimization is carried out and compared with the standard genetic algorithm, the results are shown below.

Two algorithms are used to optimize the structure of each bar, and the structure weight of the structure is reduced. The results are shown in the following diagram.

As shown, the improved genetic algorithm in optimization of structural engineering has better convergence than the traditional genetic algorithm, and in the quality optimization of the 3 pole plane truss, it has better effect and has good stability.

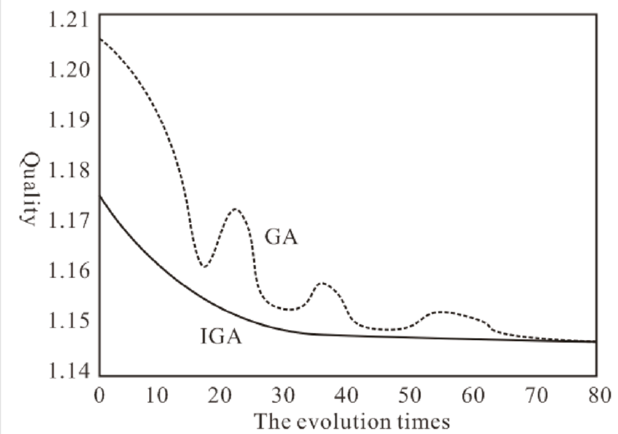

Figure 3. Optimization of truss structure

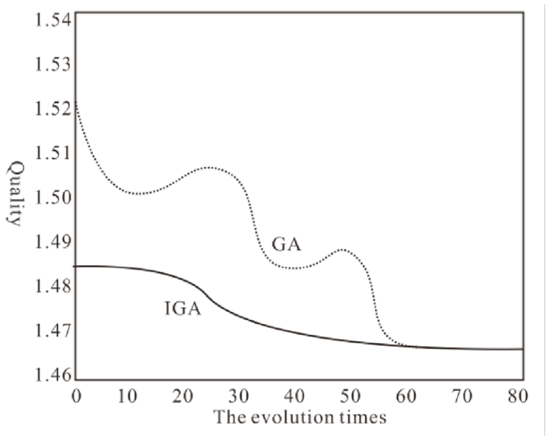

Figure 4. Overall optimization truss rod

5. Conclusion

The existing genetic algorithm in the applications of the structural engineering optimization, there are problems of premature convergence, genetic drift, and the contradictory problem between computing efficiency and diversity preservation. In view of the defects of traditional genetic algorithm, this paper puts forward the genetic algorithm of crossover operator and fitness function optimization, it can be seen from the experiment simulation results that the improved strategy puted forward this paper is effective, it greatly improve the convergence performance of the original algorithm in the optimization of structural engineering.

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