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Optimization of Stochastic System Using Genetic Algorithm and Simulation

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Optimization of Stochastic System Using Genetic Algorithm and Simulation

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Abstract

This paper presents a new method to find a optimal solution for stochastic system. This method uses Genetic Algorithm(GA) and simulation. GA is used to search for new alternative and simulation is used to evaluate alternative.

The stochastic system has one or more random variables as inputs. Random inputs lead to random outputs. Since the outputs are random, they can be considered only as estimates of the true characteristics of the system. These estimates could greatly differ from the corresponding real characteristics for the system. We need multiple replications to get reliable information on the system. And we have to analyze output data to get a optimal solution. It requires too much computation to be practical.

We address the problem of reducing computation. The procedure on this paper use GA character, an iterative process, to reduce the number of replications. The same chromosomes could exit in post and present generation. Computation can be reduced by using the information of the same chromosomes which exist in post and present current generation.

1. Introduction

If we interest in optimizing a system that have stochastic nature and is of such complexity that it is necessary to use simulation to estimate the performance of the system for each set of decision values, we have to use stochastic optimization method using simulation. Such cases arise frequently in engineering, for instance, in process design, in industrial experimentation, in design optimization, and in reliability optimization. We present a new method for finding a optimal solution to stochastic system. This method use Genetic Algorithm(GA) and simulation.

1.1 Difficulties of optimization for stochasitc system

There are difficulties of optimization for stochasitc system. Frist, because there are more complicated stochastic systems for which the objective function cannot be expressed analytically. Its cannot optimized by various techniques of mathematical programming. The systems is analyzed through simulation. Computer simulation programs are much more expensive to run than evaluating analytical functions. This makes the efficiency of the optimization algorithms more crucial.
Second, When we use simulation methodology to solve stochastic problems, we have to assign certain values to system decision variables, run simulation, analyze the output data, adjust the design variables, and run the simulation again. It is a vary complicated and time-consuming task.

2. The Stochastic Genetic Algorithm

Stochastic GA presented in this paper is stochastic optimization method using simulation, GA and Stochastic method. GA is used to search for new alternative and simulation is used to evaluate alternative and stochastic method is used to analyze output data. The structure of stochastic GA is illustrated in Figure 1.

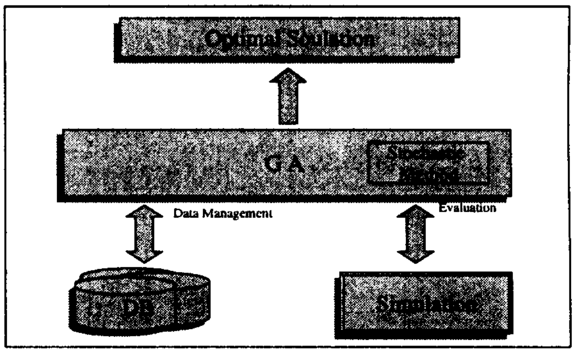

Figure 1. The structure of stochastic GA

2.1 The procedure of the stochastic GA

The output of simulation of stochastic system is considered only as estimates of the true characteristics of a model. We needs very many replications to get reliable information on a single solution in the stochastic optimization problem. It require too much computation to be practical. It is critical to reduce computation. The new stochastic GA is quickly find optimal alternative as to reduce number of replication.
The procedure of the new stochastic GA is

illustrated in Figure 2.

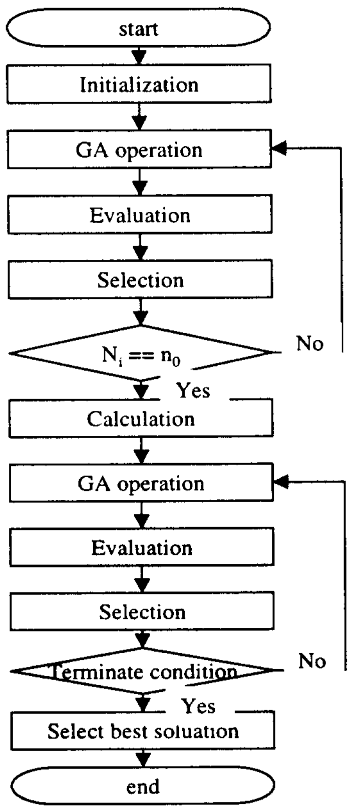

Figure 2. The procedure of the new stochastic GA

There are two stage in the procedure of stochastic GA. In the first stage we make a the initial number of replication of each chromosome, then use the resulting variance estimates to determine how many more replications from each system ate necessary in a second stage of sampling in order to reach a decision. It is similar to statistical procedure for solving stochastic systems. But it is difference in aspect in gathering sampling data and finding optimal solution.

The user-defined parameter δ is the smallest difference in expected performance that is practically significant to the user. Parameter p is a percent of population. We specially manage the top p percent of population to get optimal alternative and to reduce the number of replications. Parameter n_0 is the initial number of replications. We have to define the value of δ, overall confidence level($1-\alpha$), the

value of n_0 and the value of p before running stochastic GA algorithm.

2.1.1. The final number of replication

The final number of replications to be taken in order to meet the indifference-zone probability requirement is get by Indifference Zone Selection Approach[9]. When the replication numbers of chromosomes included in the top p percent of population is n_0, the number of replication is established. The procedure to determine the final number of replication N_i is as follows

Step 1. Let k be the number of chromosome included in top p% of the population. Find h_a for n_0, k, and α (see the tables in Bechhofer et al.[1]).

Step 2. Let X_{ij} be the output from the jth replication of solution i. Take i.i.d. sample X_{i1}, X_{i2}, X_{i3},...X_{in0} from each k chromosome of the population simulated independently.

Step 3. Calculate the sample means and marginal sample variances

$$\bar{X}_i^{(1)} = \frac{1}{n_0}\sum_{j=1}^{n_0} X_{ij}, \quad S_i^2 = \sum_{j=1}^{n_0}(X_{ij} - \bar{X}_i^{(1)})^2/(n_0 - 1)$$

Step 4. Compute the final number of replications

$$N_i = \mathrm{MAX}\ \{n_0, [\left(\frac{h_\alpha S_i}{\delta}\right)^2]\}$$

* [ ] : integer round-up function.

2.1.2. The Evaluation(Objective function)

We have to rank chromosomes to select some of them that is copied for the next generation. The evaluation of chromosome is considered only as estimates of the true characteristics of a chromosome. In a stochastic GA it is not possible to conclusively rank any population of solution without multiple replications.
Genetic Algorithm is an iterative process. we use this character to reduce the number of replications. Using information of before generations, the number of replications can be reduced. The basic idea to reduce the number of replications is that the chromosome included in the top p% of population fitness is stored and the values of its is reuse when those is required.
The process of evaluating the fitness of a chromosome consists of the following five steps:

Step 1. Convert the chromosomes genetype to its phenotype.
Step 2. Evaluate the objective function $f(x)$.
Step 3. Convert the value of objective function into fitness.
Step 4. If same chromosome is in stored chromosomes that are top p% of population in the last generation. Calculate the mean of fitness with fitness of stored chromosome. Substitute the mean of fitness for fitness obtained in Step3.

2.1.3. The Ranking

The Chromosomes is ranked after evaluating the fitness. The procedure of ranking is as follows :
Step 1. Sort the chromosomes.
Step 2. Let M is the maximum number of replication among chromosomes included in top p% of population. Find the maximum number M. If all n_i for i = 1, .. , k are equal, The procedure is finished.
Step 3. Let n_i is the replication numbers of chromosome i. Take M - n_i additional evaluations from chromosome i, for i = 1, .. , k and go Step 1.
The procedure of the stochastic GA of ranking is illustrated in Figure 3.

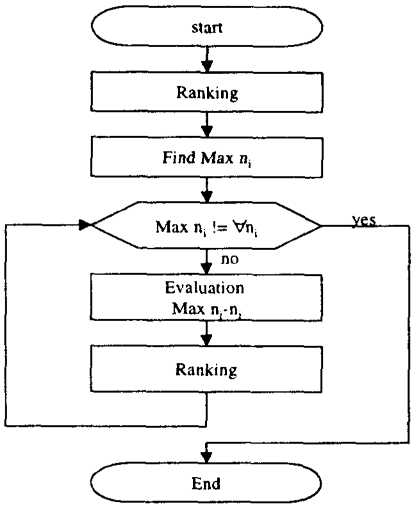

Figure 3. The procedure of ranking

2.1.4. The Selection

We use both the elitist selection method to support roulette wheel selection. The elitist selection method guarantees a certain number of high fitness individuals will propagate to the next generation, and decreases stochastic errors. Elitist selection ensures that the best chromosome is passed onto the new generation if it is not selected through the process of roulette wheel selection.

3. Example

The following discrete minimization problems were used as a test battery. This set of problems are those used in [10].

Object Function :

$$\text{Min } (x_1-8)^2+(x_2-12)^2+\varepsilon_1$$

Subject to :

$$0 \le x_i \le 127,\ i=1,2.$$

ε_1 is a normal distributed random variable with zero mean and a standard deviatin of 100. This random variable is added to each function to give them stochastic characteristics. The value of Indifference Zone δ is 1. And confidence level($1-\alpha$) is 95%. The initial number of replications are 40. The final number of replications N_i that we get in the procedure are 351. The Table 1 is represented as the result.

Generation	X1	X2	mean	Generation	X1	X2	mean
1	8	6	50.0	2	6	18	40.4
3	8	18	35.0	4	8	15	6.2
5	6	9	7.2	6	6	13	6.9
21	6	13	1.8	22	8	11	0

Table 1. The result of example

We quickly get the optimal solution point(8, 11) and the expected optimal value(0).

4. Conclusion

We present the new method for getting the optimal solution of stochastic system. This method quickly find optimal solution and give guarantee for optimal solution.

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