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Full Length Research Paper

An improved genetic algorithm for solving simulation optimization problems

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Simulation optimization studies the problem of optimizing simulation-based objectives. Simulation optimization is a new and hot topic in the field of system simulation and operational research. To improve the search efficiency, this paper presents a hybrid approach which combined genetic algorithm and local optimization technique for simulation optimization problems. Through the combination of genetic algorithms and with the local optimization method, it can maximally use the good global property of random searching and the convergence rate of a local method. This study considers the sampling procedure based on orthogonal design and quantization technology, the use of orthogonal genetic algorithm with quantization for the global exploration, and the application of local optimization technique for local exploitation. The final experimental results demonstrated that the proposed approach can find optimal or close-to-optimal solutions, and is superior to other recent algorithms in simulation optimization.

Key words: Simulation optimization, genetic algorithms, local optimization, orthogonal design.

INTRODUCTION

Determining the best combination of variables to use as input for a simulation model is a common practical problem. Typically, the input values have to be chosen in a way that the cost function is optimized; the latter being computed from the model's outputs. This problem is present in several application domains where it is not possible to build a mathematical model of the system to be studied (Pierreval and Paris, 2000). In the area of manufacturing systems for example, simulation optimization is applied in many scenarios including: To optimize productive machine hours; to minimize the cost of an automated storage (retrieval) systems; to maximize the output of a computer-integrated manufacturing (CIM) systems, and to minimize station idle times in assembly line.

Several simulation optimization methods exist and have been used to solve such problems. Unfortunately, most of these methods suffer from several shortcomings, in particular: Their sensitivity to local extrema, their limitations in addressing problems with mixed numerical and non-numerical variables or high computational load. Evolutionary algorithms (EAs), which seem to be less investigated as a possible technique for the optimization of simulation models offer powerful capabilities that can avoid these shortcomings. These algorithms have been recognized as efficient tools for solving several kinds of optimization problems, including the optimization of real mathematical functions (Hindi et al., 2002) and combinatorial problems (Tsai et al., 2004). This paper examines the application of EAs to solve simulation optimization problems.

Although EAs are known to be a powerful optimization technology, they are, unfortunately, notoriously slow. In this paper, a hybrid approach combined genetic algorithm and local optimization technique is proposed to the simulation optimization problems. This study considers the sampling procedure based on orthogonal design and quantization technology, the use of orthogonal genetic algorithm with quantization for the global exploration, the application of local optimization technique for local exploitation. Through the combination of genetic algorithms and with the local optimization method, it can maximally use the good global property of random searching and the convergence rate of a local method.

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LITERATURE REVIEW

Simulation optimization is an optimization where the objective function and constraints are only available through computer simulation. Simulation optimization is broadly applied in the fields of system design and automation. Simulation optimization is currently a hot area that has attracted the attention of many researchers (Ding et al., 2005).

Simulation optimization assumes that the objective function can only be estimated through simulation. Simulation model and optimization algorithm are two important pieces to solve a simulation optimization problem. The aim of the optimization algorithm is to propose solutions to the simulation model for evaluation, which will return each solution's performance. The simulation model is stochastic and provides outputs that are translated to performance measures via expected values. Therefore, several simulation runs will be needed to evaluate the new solutions generated through the optimization algorithm at each generation. In general, simulation optimization problems can be mathematically formulated as follows:

$$Min \quad F(X) = \underset{X \in D}{E}\left[f(X, w) \right] \tag{1}$$

where f is a function of w parameterized by X , and represents the simulation objective output. The random vector w embodies all perturbations caused by uncontrollable factors. Vector X symbolizes the decision variables associated with controllable factors, and it is in general composed of discrete and continuous variables with values in the solution space D . $F(X)$ is a function representing the conditional expected value of the simulation objective output for a given X .

It has been proven that a general simulation optimization problem cannot be solved in a finite number of steps. The simulation optimization problem extensively exists in science and engineering fields. Finding the global optimal solution of such problems is unsolved by using mathematical method. Although local optimization techniques have been very sophisticated and well documented, they can only guarantee to produce a local optimal solution, unless a starting point is sufficiently close to a global optimal solution (Yang et al., 2005). Once an objective function has many local extreme points, the existing optimization methods may not obtain the global optimization efficiently.

In recent year, a number of deterministic and stochastic algorithms have been proposed for solving the simulation optimization problems. The stochastic algorithms may be said to start with the publications of Metropolis, Holland and Torn, which are pioneering to the full development and applications of the stochastic algorithms, in particular, simulated annealing (SA), genetic algorithms (GA) and multi-start approach, in the last three decades (Cohn and Fielding, 1999; Tu and Mayne, 2002a, b). In general, the computational results of the stochastic methods are better than those of the deterministic method.

The GA provides a robust procedure not only to explore broad and promising regions of solutions but to avoid being trapped at the local optimization (Leung and Wang, 2001). But, GA cannot theoretically guarantee to always produce a global optimal solution, unless the number of samplings tends to (practically impossible) infinity. A number of hybrid global optimization algorithms have been proposed by combining GA with a local optimization method (Kaveh and Rahami, 2006) in order to maximally use the good global property of random searching and the convergence rate of a local method. Gerstoft suggested incorporating the Gauss-Newton method into GA in order to improve every member of the new generation. At the same time, many innovative models and novel approaches based on GA were proposed to solve global optimization problem recently (Amirjanov, 2004; Chelouah and Siarry, 2000; Li et al., 2002; Tu and Lu, 2004; Xing et al., 2006).

Among these improved approaches, Leung and Wang designed the orthogonal genetic algorithm with quantization (OGA/Q) for global numerical optimization with continuous variables (Leung and Wang, 2001). The final experimental results suggest that OGA/Q achieved the significantly better results than many published improved GA. Also, Xing et al. proposed an improved orthogonal genetic algorithm with quantization (IOGA/Q) (Xing et al., 2009). They constructed a novel mutation operator based on the immunity operation. Experiments with IOGA/Q on many test functions resulted in near-optimal solutions in all cases. In comparison with several other algorithms, IOGA/Q achieved improved accuracy. According to our experimental results, the local optimization capability of OGA/Q and IOGA/Q is inefficient when solving the simulation optimization problems.

In this paper, a hybrid approach combined genetic algorithm and local optimization technique will be presented for solving simulation optimization problems. In this proposed hybrid approach, we applied orthogonal design and quantization technology to sample from the feasible domain firstly, and executed the global exploration using orthogonal genetic algorithm with quantization secondly, then implemented local exploitation through local optimization technique. The optimization performance of this proposed approach has been improved largely by efficaciously integrating the orthogonal design, quantization technology, genetic algorithm and local optimization method together.

THE PROPOSED IMPROVED GENETIC ALGORITHM

Here, we present our proposed improved genetic algorithm for solving the simulation optimization problems detailedly. The

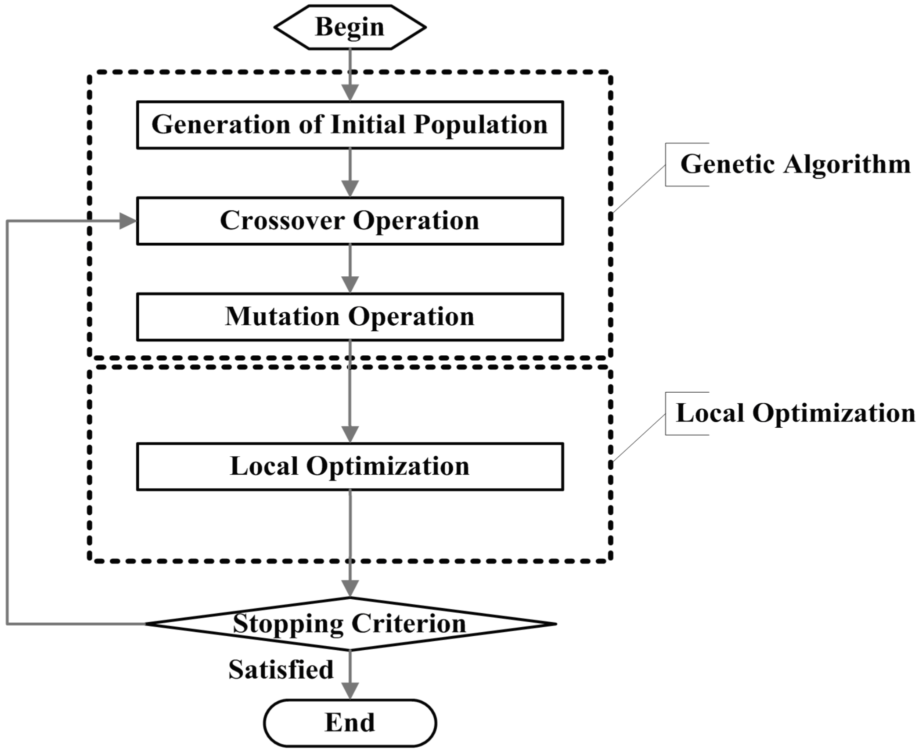

Figure 1. Optimization framework of this proposed IGA.

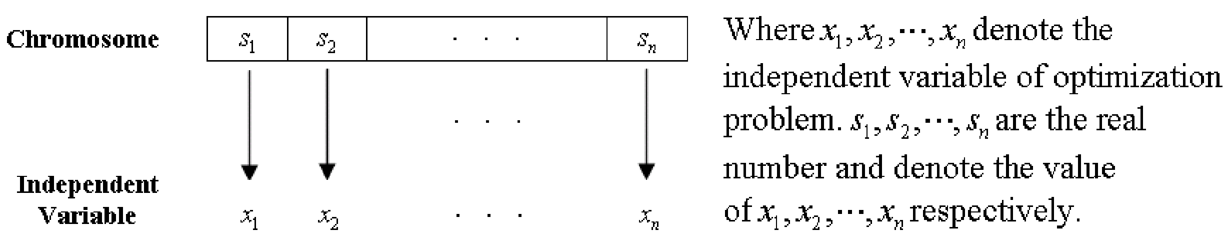

Figure 2. The mechanism of floating point representation.

difference between our approach and OGA/Q can be summarized as follows. At first, an improved mutation operator was constructed in this approach. Secondly, the local optimization method was integrated to this proposed approach.

This proposed hybrid approach, called improved genetic algorithm (IGA), can be briefly sketched as follows. At first, it gained the initial population through sampling from the feasible domain by using orthogonal design and quantization technology; secondly, it evolved the current population through orthogonal genetic algorithm with quantization; thirdly, it applied the local optimization technique to refine the current best solution. The computational flow of this proposed HGA is displayed in the Figure 1.

Generation of initial population

Coding and decoding is a time-consuming procedure. Also, if the length of solution (chromosome) is too long, then it should have enough memory for the giving computation. To decrease computing time furthest and control the length of solution effectively, we use the floating point representation in this proposed IGA. The chromosomes are the arrays of real number instead of bit strings (the coding and decoding procedures, necessary for the binary-coded GA, are then avoided). The length of chromosome is the amount of independent variable of optimization problem. Figure 2 illustrates the mechanism of floating point representation.

Before an optimization problem is solved, we may have no information about the location of the global minimum. It is desirable that the chromosomes of the initial population be scattered uniformly over the feasible solution space, so that the algorithm can explore the whole solution space evenly. Therefore, it gained the initial population through sampling from the feasible domain by using orthogonal design and quantization technology.

Crossover operation

A crossover operator recombines the gene-codes of two parents

Parent Chromosome X	37.21453698643	-0.12345678901	
Children Chromosome X_1	37	-0	Round at 0^{th} place after radix point
Children Chromosome X_2	37.2	-0.1	Round at 1^{st} place after radix point
Children Chromosome X_3	37.21	-0.12	Round at 2^{nd} place after radix point
Children Chromosome X_4	37.215	-0.123	Round at 3^{rd} place after radix point
Children Chromosome X_5	37.2145	-0.1235	Round at 4^{th} place after radix point
Children Chromosome X_6	37.21454	-0.12346	Round at 5^{th} place after radix point
Children Chromosome X_7	37.214537	-0.123457	Round at 6^{th} place after radix point
Children Chromosome X_8	37.2145370	-0.1234568	Round at 7^{th} place after radix point
Children Chromosome X_9	37.21453699	-0.12345679	Round at 8^{th} place after radix point
Children Chromosome X_{10}	37.214536986	-0.123456789	Round at 9^{th} place after radix point

Select a best chromosome among these 11 chromosomes as the result of this mutation.

Figure 3. An example of our new proposed mutation operation.

and produces offspring such that the children inherit a set of building blocks from each parent. On the one hand, we want to obtain enough potential offspring for improving the current population; on the other hand, each pair of parents should not produce too many potential offspring in order to avoid a large number of function evaluations during selection. As you know, it is very pivotal to select a small, but representative sample of points as the potential offspring. For this purpose, we use the new proposed operator, orthogonal crossover with quantization (Leung and Wang, 2001), as the crossover operator of IGA.

Mutation operation

Mutation takes place on some newly formed children in order to prevent all solutions from converging to their particular local optima. According to traditional ways, to perform mutation on a chromosome, it randomly generates an integer $j \in [1, N]$ and a real number $z \in [l_j, u_j]$, and then replaces the j^{th} component of the chosen chromosome by z to get a new chromosome. But, this traditional mutation is inefficient for solving the complex global optimization problem. In this paper, we present a new mutation mechanism for our proposed IGA. We apply the round operation to implement our new mutation. Figure 3 is an example of our proposed mutation operation.

In the proposed IGA algorithm, the floating point representation is applied to represent the individual. That is, the value of each variable will be denoted by a float number. Since the configuration of computer is more powerful than before, the value of float number is more detail than before, e.g., 37.21453698643 or -0.12345678901. Suppose that the optimal value of one variable is 37.2, it is very difficult to obtain this value in such detail environment. For this reason, it is necessary to introduce the round operation into the mutation operation. In this proposed IAG algorithm, an improved mutation is proposed based on the mutation. As the aforementioned analysis, this novel mutation operator is helpful to obtain some optimal solution.

Local optimization

In GA, the generated solutions by genetic operators may be so coarse that they should be improved by some complementary local optimization method. In this paper, we apply an effective steepest descent method to refine the near-optimal solutions achieved by GA. We only refine the global excellent solution (the most excellent solution from the beginning of the trial) at each generation.

EXPERIMENTAL RESULTS

Here, the proposed approach is demonstrated by a simulation optimization problem. The experiments were performed on a Pentium IV 2.4 GHz personal computer with a single processor and 512M RAM. To avoid the randomness in the optimization process, each experiment was run 50 times. The parameter settings for the OGA/Q used in this paper are listed in Table 1.

In order to simplify subsequent computations, we only consider single objective simulation optimization problems in this part. In fact, the appropriate approach can reduce multi-objective simulation optimization problems to single objective simulation optimization problems. Given the case of intercommunion at future, a complex function is used to replace the input-output relationships of the known simulation system (sub-system).

The input-output relationship of the giving simulation optimization problem is shown in Figure 4. There are five decision variables in the sub-system 1, which needs five seconds to run its practical simulation model. The time for running the simulation model of sub-system 2 is ten seconds and there has ten decision variables in the sub-system 2. We should spend twenty seconds to run the practical simulation model of sub-system 3, which has

Table 1. Parameter settings of the proposed IGA.

Parameter	Signification	Setting
Q_1	Number of quantization levels	5
B	Number of subspaces	1
G	Population size	20
Q_2	Number of quantization levels	3
F	Number of factors	4
P_c	Crossover probability	0.60
P_m	Mutation probability	0.10
$MaxGen$	Maximum iterative	100

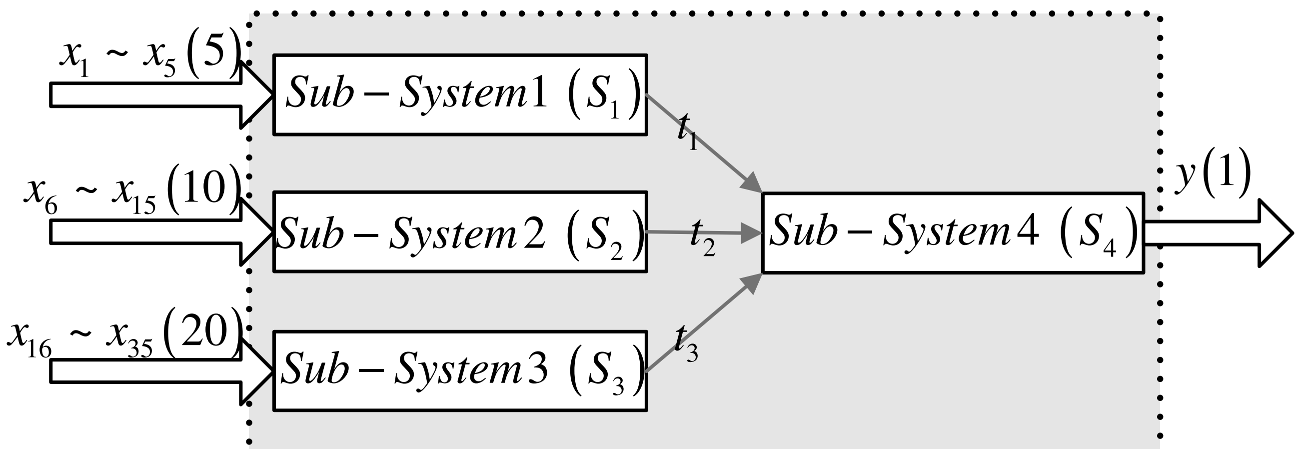

Figure 4. Input-output relationships of the simulation optimization problem.

twenty decision variables. In sub-system 4, it has three decision variables and it needs three seconds to run its practical simulation model. The complex function relationship of the giving simulation sub-systems are listed in Table 2. The feasible space (searching space or definition space) of each complex numerical function was described in Table 2 as well. Here, $Fix(x)$ rounds the elements of x to the nearest integers towards zero.

To demonstrate the efficiency of this approach, improved genetic-annealing algorithm (Lan et al., 2002), genetic algorithm-simplexes (Han and Liao, 2001), new immune GAs (Zhang and Yang, 2005), OGA/Q (Leung and Wang, 2001) and this hybrid approach were applied to solve the simulation optimization problem described in part A. These two points should be noted: (1) The five algorithms were implemented using the MATLAB language, and run in the MATLAB environment; (2) The same parameters were applied to all algorithms to avoid unintended optimization. The experiment results produced using the five different approaches for solving the simulation optimization problem are listed as Table 3.

These results show that the hybrid approach is clearly superior to the other four approaches. The results show drastic reductions in computing time using the hybrid approach and that it outperforms the other, recently developed, algorithms for simulation optimization. The proposed hybrid approach is a valuable addition to the tools available for solving simulation optimization problems, being not only feasible, correct and valid, but also fast and efficient.

Conclusions

This paper presented a hybrid approach which combined genetic algorithm and local optimization technique for simulation optimization problems. The experimental results obtained from the computational example have shown that this proposed approach is correct, feasible

Table 2. Complex function relationship of the known simulation sub-systems.

	Input-output relationship	Feasible space	Simulation time (S)
Sub-system 1	$S_1 = \sum_{i=1}^{5} Fix\left(x_{1i}\right)$	$0 \le x_{1i} \le 20$	5
Sub-system 2	$S_2 = \sum_{i=1}^{10} \left(x_{2i}^2 - A\cos\left(2\times\pi\times x_{2i}\right)\right)$	$A = 20$ $-1 \le x_{2i} \le 1$	10
Sub-system 3	$S_3 = \frac{1}{20}\sum_{\text{i}=1}^{20}\left(x_{3i}^4 - 16x_{3i}^2 + 5x_{3i}\right)$	$0 \le x_{3i} \le 5.5$	20
Sub-system 4	$S_4 = \max\left\{\sum_{i=1}^{3} S_i \sin(\sqrt{\lvert S_i \rvert})\right\}$	$0 \le S_i \le 100$	3

Table 3. Experiment results produced using the different approaches.

Name of different approaches	Optimization result	Simulation time (h)
Improved genetic-annealing algorithm	127.76	794.41
Genetic algorithm-simplexes	179.64	151.55
New immune GAs	185.81	170.89
OGA/Q	186.62	255.12
This proposed hybrid approach	190.61	28.66

and efficacious.

The future researches are summarized as follows: Improve the performance of this proposed approach, and applying it to solve other engineering problems.

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