〈硏究報告〉

Journal of the Korean Institute of Industrial Engineers
Vol. 13, No. 1, June. 1987

Evaluation of the Simulation Optimization Tool, SIMICOM

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Abstract

A tool for optimizing simulated discrete variable stochastic systems, SIMICOM was developed and presented in [5]. In this paper an evaluation of its performance and results of comparisons with other popular methods for dealing with simulation-optimization problems will be provided. Based on several test problems it is concluded that SIMICOM dominates those methods.

1. Introduction

A heuristic algorithm(SIMICOM) has been designed for optimizing simulated stochastic systems whose performances are functions of several discrete decision variables[1]. The approach adopted utilizes an integer complex method coupled with techniques of establishing confidence intervals for the system's responses.

It can handle a general class of optimization problems using computer simulation that could be constrained or unconstrained. In constrained cases, the constraints could either be explicit analytical functions of decision variables or be expressed as other responses of the simulation model. It also considered the economic aspect of obtaining the solution in addition to get a reasonably accurate solution. In this paper the comparative results of the proposed method with two other methods, Integer Gradient Search Method and Random Search Method based on several known stochastic functions and simulation models are demonstrated.

2. Test Problems

To evaluate the performance of the proposed method, five known stochastic functions (some from[4])and two simulation models[2, 6] in Table 1 were used as test battery.

2.1 Unconstrained Problems

In this case bound constraints for each problem were selected as follows:
For problems #1, #2, #3, #4
$-25 \leq x_i \leq 50, \quad i = 1, 2$

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For problems #5

$-25 \leq x_i \leq 50$, i = 1, 2, 3, 4

For problem #6

$1 \leq x_1 \leq 12$

$1 \leq x_2 \leq 15$

$1 \leq x_3 \leq 10$

$1 \leq x_4 \leq 5$

For problem #7 the unconstrained version is trivial because of the nature of the problem. Thus, only the contrained one is considered. Each alternative point in problem #1 through #5 was evaluated with noise function, e_1, where e_1 is normally distributed with a mean of zero and a standard deviation of 100. Run lengths, 60, 100,20 are used as initial, terminal and incremental run length respectively for SIMICOM. Run length 100 is used for other methods. Note that this creates an advantage for other methods because the average run length used by SIMICOM will be smaller than 100. However, as will be shown, even with this disadvantage SIMICOM performs better than those methods.

Table 1. Several stochastic functions and Models for Testing

problem	function or model	optimum	value of objective function at optimum
#1	$(x_1^2/2-8)^2+(x_2-12)^2+e_1$	(16, 12)	0
#2	$\{(x_1^2+x_2-11)^2+(x_1+x_2^2-7)^2\}^{1/2}/3+e_1$	(3, 2)	0
#3	$\{(x_2-x_1^2)^2+(1-x_1)^2\}^{1/2}+e_1$	(1, 1)	0
#4	$\{(9x_1^2+2x_2^2-11)^2+(3x_1+4x_2^2-7)^2\}^{1/2}+e_1$	(1, 1), (1, -1)	0
#5	$\{(x_1+10x_2)^2+5(x_3-x_4)^2+(x_2-2x_3)^4 +10(x_1-x_4)^4\}/18+e_1$	(0, 0, 0, 0)	0
#6	robotic manufacturing cell model in [6]	unknown	unknown
#7	flexible manufacturing system model in [2]	unknown	unknown

2.2 Constrained Problems

To build constrained problems, the following constraints were imposed on each problem:

For problem #1, #2, #3, #4

$1 \leq x_i \leq 50$, i = 1, 2

$x_1 + x_2 \leq 70$

$(x_1-23)^2+(x_2-23)^2+e_2 \leq 800$

For problem #5

$1 \leq x_i \leq 25$, i = 1, 2, 3, 4

$3x_1+x_2+x_3+4x_4 \leq 100$

$(x_1-10)^2+(x_2-10)^2+(x_3-10)^2+(x_4-10)^2+e_2 \leq 300$

Each point in problems #1 through #5 was evaluated with noise functions, e_1 and e_2, where

e_1 is the same noise function as in the unconstrained problem and e_2 is normally distributed with a mean of zero and a standard deviation of 20.

For problem #6

$1 \leq x_1 \leq 10$

$1 \leq x_2 \leq 8$

$1 \leq x_3 \leq 12$

$1 \leq x_4 \leq 3$

$2x_1 + 3x_2 + x_3 + 5x_4 \leq 45$

Expected production rate per hour $\geq$ 50 units

For problem #7

$1 \leq x_1 \leq 10$

$1 \leq x_2 \leq 10$

$1 \leq x_3 \leq 10$

$1 \leq x_4 \leq 10$

$1 \leq x_5 \leq 20$

$x_1 + 1.5x_2 + 2x_3 + 3x_4 \leq 50$

Expected utilization of machines ≥ 0.6

3. Selected Methods

To evaluate the power of SIMICOM, its performance was compared to those of Integer Gradient Method(INGR) and Random Search Method(RAN). The reason for this choice is that these methods are the most often used techniques by analysts to solve discrete optimization problem.

3.1 Integer Gradient Search Method(INGR)

The gradient search method for the continuous variable problem has been modified in[4] for unconstrained nonlinear integer programming problems. Among the available versions of the Integer Gradient Method, the two-sided gradient approximation has been applied to the discrete problems under study. The summary of the procedure used is as follows:

A two-sided gradient approximation at the current point is used to determine a search direction similar to those for continuous variable techniques. The only difference is that the gradient is approximated by evaluating discrete points. The search direction generated is then transformed into an integer direction which contains discrete points. Next, a one–dimensional search is applied to locate an optimum point along this direction. Sometimes a premature termination may result when the search overshoots the optimum. In this case, a subsequent search is initiated to overcome this difficulty. In this search several points in the vicinity of the current point, that are not precisely on the line of search, are evaluated. The details of this process are given in [4]. Finally the search is terminated when nobetter point can be found in the integer gradient direction.

The starting point used for Integer Gradient Search is the same point that is found by SIMICOM via a uniform search. This is an advantage for INGR because the capabilities of SIMICOM in finding the starting point has been used in INGR's favor. Instead, the number of simulation runs for finding the starting point is charged to INGR.

3.2 Random Search Method(RAM)

There are several variations of this technique. The simplest one is to choose at random a number of sets of values for controllable variables and hope one of them will provide the optimum response. The procedure used here is as follows. Using the ranges from the bound constraints, a feasible value for each variable is selected at random. If the problem is constrained, before running the simulation model the randomly selected alternative point is tested for its feasibility with respect to the explicit constraints. If this point satisfies all the explicit constraints, then the simulation model is run using this point and the system responses are obtained. Otherwise, this point is dropped and another point is picked at random. If implicit constraints exist, after obtaining system responses, they are checked against these constraints. If the point satisfies all the implicit constraints, then its response for the objective function is compared with current optimal value for the objective function. If the result is better, the new point is selected as the new optimum. Otherwise the old optimum is retained and the procedure is repeated.

The number of simulation runs and the starting point for Random Search Method(RAN), are the same as those used in applying SIMICOM. The sequential procedure for running the simulation model discussed in [5] is adopted for economical use of computer time.

4. Gain Function

Although in both SIMICOM and INGR algorithms the user specifies the maximum number of simulation runs, the number of simulation runs used cannot be controlled. For this reason, for each optimum obtained a gain function similar to the one used in [3] is defined as follows:

$$G = | (Rf-Rs)/\{N(Ro-Rs)\} |$$

Where

G=Gain per simulation run in terms of the ratio of the achieved improvement to the possible improvement.

Rf=The true response found as optimum by the search method.

Rs=The true response at the starting point

Ro=The true response at the real optimum

N=Number of Simulation Runs(Simulated Alternatives)

Since in real simulated systems the real optimum is unknown, the definition of the gain function is modified as:

$$G \doteq | (Rf-Rs)/N |$$

5. Comparative Results

The results for the test problems are shown in Tables 2 through 5. From these Tables following observations can be made.

(1) The gain by SIMICOM is larger than that of INGR for all problems. The ratio of gain by SIMICOM to gain by INGR ranges from 1.038 for problem #7 to about 21.37 for problem #2 unconstrained(See Table 2). From Tables 3 and 4 it is seen that in all cases SIMICOM has found better solutions than the ones found by INGR.And in one case INGR has not

found a better solution than even the starting point.

(2) By looking at Tables 2, 3 and 5 it is found that in eleven cases out of thirteen SIMICOM has found better solutions than the ones found by RAN. In four of the cases RAN has not made any improvements even after using a number of simulation runs equal to those used by SIMICOM. The fact that Random Search obtained better gains than SIMICOM in a few cases requires an explanation. In the preceding tables inconsistency of the random search is demonstrated through its range of performance(See Table 2). This inconsistency may sometimes result in a better than expected result. However, this happens by chance only and could not be considered an advantage, because one will never be able to trust the result.

According to the results for the problems used, one can conclude that SIMICOM is more reliable than Integer Gradient Method and Random Search Method.

Table 2 . Comparison of Results by SIMICOM, INGR and RAN

Problem	G1	G2	G3	G1 / G2	G1 / G3
# 1 U	·0500	·0000	·0000	∞	∞
C	·0712	·0647	·0598	1.100	1.190
# 2 U	·0577	·0027	·0000	21.37	∞
C	·0615	·0585	·0662	1.051	·9290
# 3 U	·0827	·0503	·0766	1.644	1.079
C	·1637	·0766	·1643	2.137	·9963
# 4 U	·0769	·0355	·0000	2.166	∞
C	·0498	·0466	·0493	1.068	1.010
# 5 U	·0270	·0189	·0000	1.428	∞
C	·0436	·0319	·0182	1.367	2.396
# 6 U	·0232	·0184	·0018	1.261	12.88
C	·0250	·0123	·0057	2.032	4.386
# 7 C	·1716	·1653	·1433	1.038	1.197

G1:Gain by SIMICOM
G2:Gain by INGR
G3:Gain by RAN
U :Unconstrained Problem
C :Constrained Problem

Table 3. Optima Found by SIMICOM for Test Problems

prob.	Xs	Rs	Xo	Ro	Xf	Rf	N	G
# 1 U	(12, 12)	4.00	(16, 12)	0	(18, 12)	1.00	15	·0500
C	(25, 25)	325.25	(16, 12)	0	(15, 13)	1.25	14	·0712
# 2 U	(12, 12)	69.30	(3, 2)	0	(−5, −5)	5.27	16	·0577
C	(25, 25)	302.17	(4, 3)	3.33	(7, 8)	26.27	15	·0615
# 3 U	(12, 12)	132.46	(1, 1), (1, −1)	0	(0, 6)	1.00	12	·0827
C	(25, 25)	600.48	(2, 5)	1.41	(1, 13)	12.00	6	·1637
# 4 U	(12, 12)	1685.3	(1, 1)	0	(1, 1)	0.00	13	·0769
C	(25, 25)	7328.6	(3, 4)	121.49	(3, 5)	157.5	20	·0498
# 5 U	(12, 12, 12, 12)	2120.0	(0, 0, 0, 0)	0	(−1, 0, −1, −1)	·94	37	·0270
C	(7, 7, 7, 7)	462.77	(2, 1, 1, 3)	9.7	(2, 2, 2, 2)	27.78	22	·0436
# 6 U	(6, 8, 5, 3)	11.72	−	−	(10, 10, 6, 4)	10.93	34	·0232
C	(5, 4, 6, 2)	13.33	−	−	(5, 4, 4, 2)	12.63	28	·0250
# 7 C	(5, 5, 5, 5, 10)	19.73	−	−	(7, 3, 3, 7, 5)	11.49	48	·1716

*X_s : Starting point
X_f : Optimum found
X_o : True optimum

Table 4. Optima Found by INGR for Test Problems

Prob.	Xs	Rs	Xo	Ro	Xf	Rf	N	G
# 1 U	(12, 12)	4.00	(16, 12)	0	(12, 12)	4.00	19	·0000
C	(25, 25)	325.25	(16, 12)	0	(15, 15)	9.25	15	·0647
# 2 U	(12, 12)	69.30	(3, 2)	0	(14, 7)	66.67	14	·0027
C	(25, 25)	302.17	(4, 3)	3.33	(5, 15)	74.96	13	·0585
# 3 U	(12, 12)	132.46	(1, 1), (1, −1)	0	(−2, 9)	5.83	19	·0503
C	(25, 25)	600.48	(2, 5)	1.41	(5, 24)	4.12	13	·0766
# 4 U	(12, 12)	1685.3	(1, 1)	0	(0, 1)	9.49	28	·0355
C	(25, 25)	7328.6	(3, 4)	121.49	(1, 8)	281.7	21	·0466
# 5 U	(12, 12, 12, 12)	2120.0	(0, 0, 0, 0)	0	(12, −1, 1, 12)	38.33	52	·0189
C	(7, 7, 7, 7)	462.77	(2, 1, 1, 3)	9.7	(9, 1, 1, 10)	43.17	29	·0319
# 6 U	(6, 8, 5, 3)	11.72	−	−	(9, 11, 8, 5)	11.04	37	·0184
C	(5, 4, 6, 2)	13.33	−	−	(4, 5, 6, 2)	12.96	30	·0123
# 7 C	(5, 5, 5, 5, 10)	19.73	−	−	(3, 7, 4, 7, 5)	11.63	49	·1653

Table 5 . Optima Found by RAN for Test Problems

Prob.	Xs	Rs	Xo	Ro	Xf	Rf	N	G
# 1 U	(12, 12)	4.00	(16, 12)	0	(12, 12)	4.00	15	·0000
C	(25, 25)	325.25	(16, 12)	0	(2, 14)	53.00	14	·0598
# 2 U	(12, 12)	69.30	(3, 2)	0	(12, 12)	69.30	16	·0000
C	(25, 25)	302.17	(4, 3)	3.33	(5, 2)	5.37	15	·0662
# 3 U	(12, 12)	132.46	(1, 1), (1, −1)	0	(−6, 44)	10.63	12	·0766
C	(25, 25)	600.48	(2, 5)	1.41	(2, 14)	10.05	6	·1643
# 4 U	(12, 12)	1685.3	(1, 1)	0	(12, 12)	1685.3	13	·0000
C	(25, 25)	7328.6	(3, 4)	121.49	(5, 2)	223.3	20	·0493
# 5 U	(12, 12, 12, 12)	2120.0	(0, 0, 0, 0)	0	(12, 12, 12, 12)	2120.	37	·0000
C	(7, 7, 7, 7)	462.77	(2, 1, 1, 3)	9.7	(1, 7, 3, 1)	281.2	22	·0182
# 6 U	(6, 8, 5, 3)	11.72	−	−	(6, 8, 6, 3)	11.66	34	·0018
C	(5, 4, 6, 2)	13.33	−	−	(5, 4, 5, 2)	13.17	28	·0057
# 7 C	(5, 5, 5, 5, 10)	19.73	−	−	(3, 7, 3, 7, 6)	12.85	48	·1433

6. Concluding Remarks

In this paper a tool, SIMICOM, for optimization of discrete variable stochastic systems which are modeled through computer simulation has been tested and compared with two other methods. The results from the comparison showed that the SIMICOM is a very effective tool for optimizing simulated systems and more reliable than two other methods.

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