

1978

SBOPT: A Simulation Based Optimization Algorithm

B. A. Dendrou

S. A. Dendrou

Elias N. Houstis

Purdue University, enh@cs.purdue.edu

Report Number:

78-274

Dendrou, B. A.; Dendrou, S. A.; and Houstis, Elias N., "SBOPT: A Simulation Based Optimization Algorithm" (1978). *Department of Computer Science Technical Reports*. Paper 206.
<https://docs.lib.purdue.edu/cstech/206>

This document has been made available through Purdue e-Pubs, a service of the Purdue University Libraries.
Please contact epubs@purdue.edu for additional information.

SBOPT: A SIMULATION BASED OPTIMIZATION
ALGORITHM

S. A. Dendrou*, B. A. Dendrou*, E. N. Houstis**

CSD-TR 274
July 1978

Abstract

A common problem encountered in engineering practice, management science and systems analysis is to find the values of input variables which optimize some function of system performance. When systems are too complicated to be described analytically, simulation is the appropriate tool for modeling purposes. Methods of optimization through simulation have recently become a steadily growing discipline.

The present report describes a constrained optimization algorithm for a class of problems where part of the constraints consist of functional relationships between variables, determined through simulation models. This algorithm (SBOPT) utilizes sequential successive simulation approximations until the intermediary optimal solution reaches acceptable tolerance levels of discrepancy. In an example of application, the algorithm proves to converge rapidly (5-10 iterations) requiring a limited number of actual simulation performances.

*School of Civil Engineering, Purdue University, W. Lafayette, IN 47907

**Department of Computer Science, Purdue University, W. Lafayette, IN 47907

TABLE OF CONTENTS

	Page
1. Introduction	1
2. Mathematical Formulation of a Class of Optimization Problems . .	3
3. Successive Approximation Algorithm	7
4. Simulation Approximation	10
5. Convergence Considerations	13
6. Numerical Experiment	15
List of References	24
Appendix A	25
Appendix B	31

SBOPT: A Simulation Based Optimization Algorithm

1. Introduction

Optimization problems in their general form can be described by a set of variables (decision type variables) whose values have to be determined so as to optimize (maximize or minimize) a set of functions called objective functions, while satisfying a given set of equalities and inequalities, termed as constraints. A general condition for avoiding degeneracy of the problem, is that the number of variables (dimension of the decision space) be larger than the number of constraints. This in general excludes the possibility of a uniquely defined set of decision variables or, worse yet, the emptiness of the feasible space, (incompatible set of constraints). Often, the set of decision variables can be partitioned into the subsets of independent and dependent variables. The latter are also called state variables, denoting that within the set of constraints of the optimization problem are included state equations describing the relationship between independent and state variables.

The present report describes a constrained optimization algorithm for the case where the state equations are not given analytically (in closed form), but rather consist of functional relationships, determined from the output response of simulation models. Most of the recent literature focuses on the problem of the direct optimization of a simulation response. Farrell, McCall and Russel, present a state-of-the-art review in a report to the Office of Naval Research, 1975 (2). All methods developed to date are approximate and iterative in nature. A few are adaptations of gradient optimization techniques. For example,

Billes, 1974 (3), proposes a gradient technique augmented by a regression scheme. Most techniques assume unimodality of the response surfaces. Smith and Storck, 1973 (4), have performed some research in this area. Others have explicitly taken into consideration the possibility of multimodality of the response surfaces, for example Smith, 1973 (5). Yet others have used direct search methods. The fundamental problem in this optique is the reduction of the size of the search region as reported by Luss and Jaakola, 1973 (7). Another interesting aspect reported in the literature is the treatment of the experimental optimization of statistical simulation, Elridge, 1974 (6). This approach leads to yet another important aspect of simulation-based optimization, namely that of discrete set optimization. Kleijner, Naylor and Seaks, 1972 (8), used multiple ranking procedures to analyze such situations.

However, in the perspective of the present paper, the simulation-response is considered only as an implicit constraint. The situation contemplated here is often encountered in engineering practice, especially in the steadily developing field of real-time optimal control. The mathematical formulation of this class of problems is given in the following section. The core of the proposed algorithm consists of sequential successive simulation approximations, as presented in sections 3 and 4. Considerations on the convergence and stability of the proposed algorithm and a numerical experiment conclude the report.

2. Mathematical Formulation of a Class of Optimization Problems

Denoting by (X_i) the set of independent variables and by (Y_j) the set of dependent or state variables, a class of simulation-based constrained optimization problems can be formulated as follows:

$$\text{Opt}_{X_i} \quad Z = Z(X_i, Y_j) \quad (2-1)$$

$$\text{s.t.} \quad Y_j = r_j(X_i) \quad \forall j \quad (2-2)$$

$$g_\ell(X_i, Y_j) \begin{matrix} \leq \\ > \end{matrix} 0; \quad \forall \ell \quad (2-3)$$

$$i=1, \dots, n; \quad j=1, \dots, m; \quad \ell=1, \dots, k$$

Z in Eq. (2-1) is the objective function which is a function of both sets of variables (X_i) and (Y_j) . It is to be optimized over both sets of variables (X_i) and (Y_j) . r_j in Eq. (2-2) denotes the 'm' functional relationships between input and output response of the state-variable simulation. Finally g_ℓ , Eq. (2-3), denotes the set of 'k' equality and inequality constraints that define the feasible space for the decision variables. g_ℓ depend on both sets of variables (X_i) and (Y_j) .

Were the functional relationships r_j , Eq. (2-2), to be known, a direct substitution into Eqs. (2-1) and (2-3) would transform the problem to a standard constrained optimization one, over the set of variables (X_i) . A natural alternative then would be to find approximations to the r_j 's. However, the simulation-response surfaces usually display high non-linearities. Satisfactory approximations could prove costly in such situations.

At the other end of the spectrum, relaxing the functional constraints (2-2) is equivalent to solving an alternate constrained optimization problem over both sets of variables (X_i) and (Y_j) . Solving this latter problem has the advantage of detecting the vicinity of potentially useful

(X_i) -points. The proposed algorithm SBOPT takes advantage of both above situations by iteratively constraining the feasible space through successive approximations of the functional relationships $r_j(X_i)$, Eq. (2-2).

Schematically, the above discussion can be illustrated as shown in fig. 2.1. Denoting by Ω_x the feasible decision space as defined by Eq. (2-3), Fig. 2.1.a, its image Ω_x^{-1} in the state space can be determined through the mapping, Fig. 2.1.b.

$$r_j : X_i \rightarrow Y_j \quad (2-4)$$

Likewise, denoting by Ω_y the feasible state-space as defined by Eq. (2-3), Fig. 2.1.b, its image by the inverse mapping r_j^{-1} , denoted Ω_y^{-1} produces an additional restriction to the decision space, Fig. 2.1.a. The intersection of the above domains, define the overall feasible space, respectively in the decision and state space, Fig. 2.1.a,b. However, the mapping r_j is defined by the simulation model only in the direction $X_i \rightarrow Y_j$. Thus, the inverse image Ω_y^{-1} cannot be readily defined. This is in essence the difficulty of the simulation-based optimization situations.

On the other hand, optimizing Z in the X, Y -space, Fig. 2.1.c, over both sets of variables considered as independent (neglecting Eq. 2-2), produces the point (X_i^*, Y_j^*) . The actual simulation-response corresponding to X_i^* being $Y_j(X_i^*)$, a natural measure of the discrepancy is given by the following norm:

$$||Y_j^* - Y_j(X_i^*)|| \quad (2-5)$$

The decrease of the above norm constitutes a natural criterion of convergence of an iterative scheme for the solution of the optimization problem. Moreover, the actual simulation-response points $Y_j(X_i^*)$ could be used to successively improve a simulation-response approximation. Such a scheme could have the potential advantage of reducing the number of

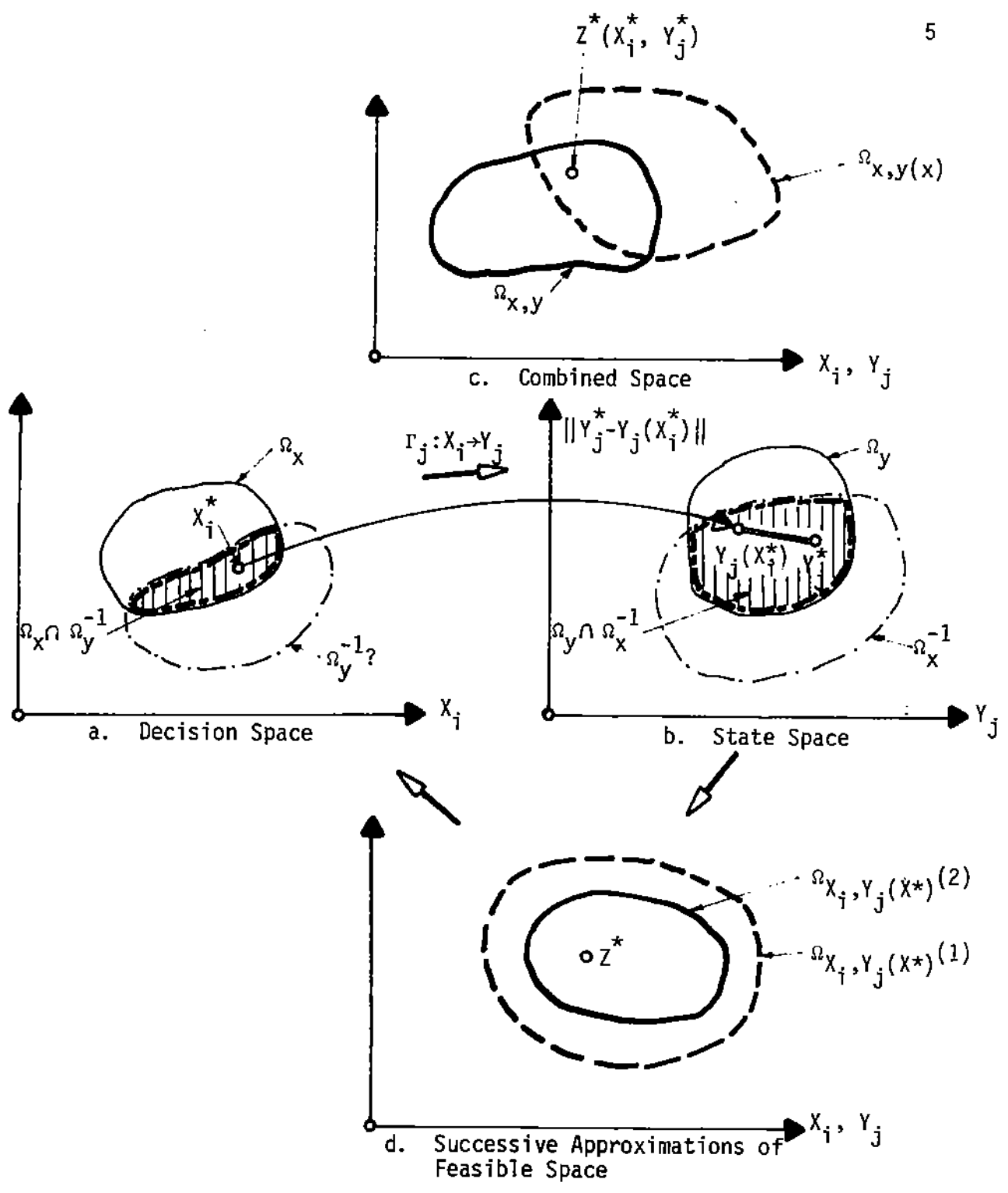


FIGURE 2.1 ILLUSTRATION OF OPTIMIZATION IN DECISION SPACE AND STATE SPACE

simulation runs, strictly to the number of iterations, if the algorithm is proven to converge. This advantage can be measured by comparing the above scheme with the 'brutal force' heuristic-search method, for example using Box's Complex algorithm, (1). This algorithm proceeds through a series of 'complexes' (sets of feasible points), formed by substituting successively the worst among the points of the 'complex', by an improving point. Each point evaluation requiring one simulation run, the total number of such runs would be equal to the total number of point evaluations. It usually runs in the prohibitive order of hundreds.

A pertinent question at this point, is that of the topologic relationship between the different feasible spaces illustrated in Figure 2.1. In fact it can be seen that the following relationship of inclusion holds:

$$\Omega_{x,y(x)} \subset \Omega_{x,y} \quad (2-6)$$

since the approximate space $\Omega_{x,y}$ disregards one of the conditions of $\Omega_{x,y(x)}$, namely Eq. (2-2). Thus, a temporary solution to the problem of iteration 'i' may prove to be infeasible. A condition for the convergence of the algorithm would be that the space $\Omega_{x,y}$ "shrinks" between successive iterations until it coincides with $\Omega_{x,y(x)}$ within acceptable tolerance limits.

3. Successive Approximation Algorithm

In the light of the above discussion, the following algorithm is proposed. It takes advantage of the comparatively easy initial determination of a suboptimal set of points (X_i^*) and (Y_j^*) , by neglecting the simulation-response conditions, Eq. (2-2). Such a suboptimization can be performed by any standard Mathematical Programming technique, since all the remaining relations, Eqs. (2-1) and (2-3) are analytic. The simulation model can be called for a patterned set of points in the neighborhood of the above initial suboptimal point (X_i^*) and (Y_j^*) . Alternatively, the simulation-response can be approximated locally, within the above suboptimal neighborhood, on the basis of the patterned simulation runs. Subsequently, a new optimization problem can be exactly solved, consisting of the initial problem augmented by the approximation to the simulation-response. The thus generated refined suboptimal point can be used in turn to refine the simulation response, and so on recursively until an acceptable convergence is achieved. Such a scheme is illustrated in the flowchart of Fig. 3.1.

In the scheme of the algorithm SBOPT, the standard constrained optimization method 'COMPLEX' of Box, (1), is used in the suboptimization for illustrative purposes. Between successive iterations, the following feature is introduced in addition to the scheme of the above discussion. All intermediary outcomes X^* and Y^* are saved along with the corresponding real simulation responses in arrays Y and YST (see Appendix A). All intermediary entries to array YST are sorted in an increasing order of the corresponding discrepancies, so that only the best among the known points are retained for the simulation approximation in the following iteration. However, in order to avoid cycling of the algorithm, new

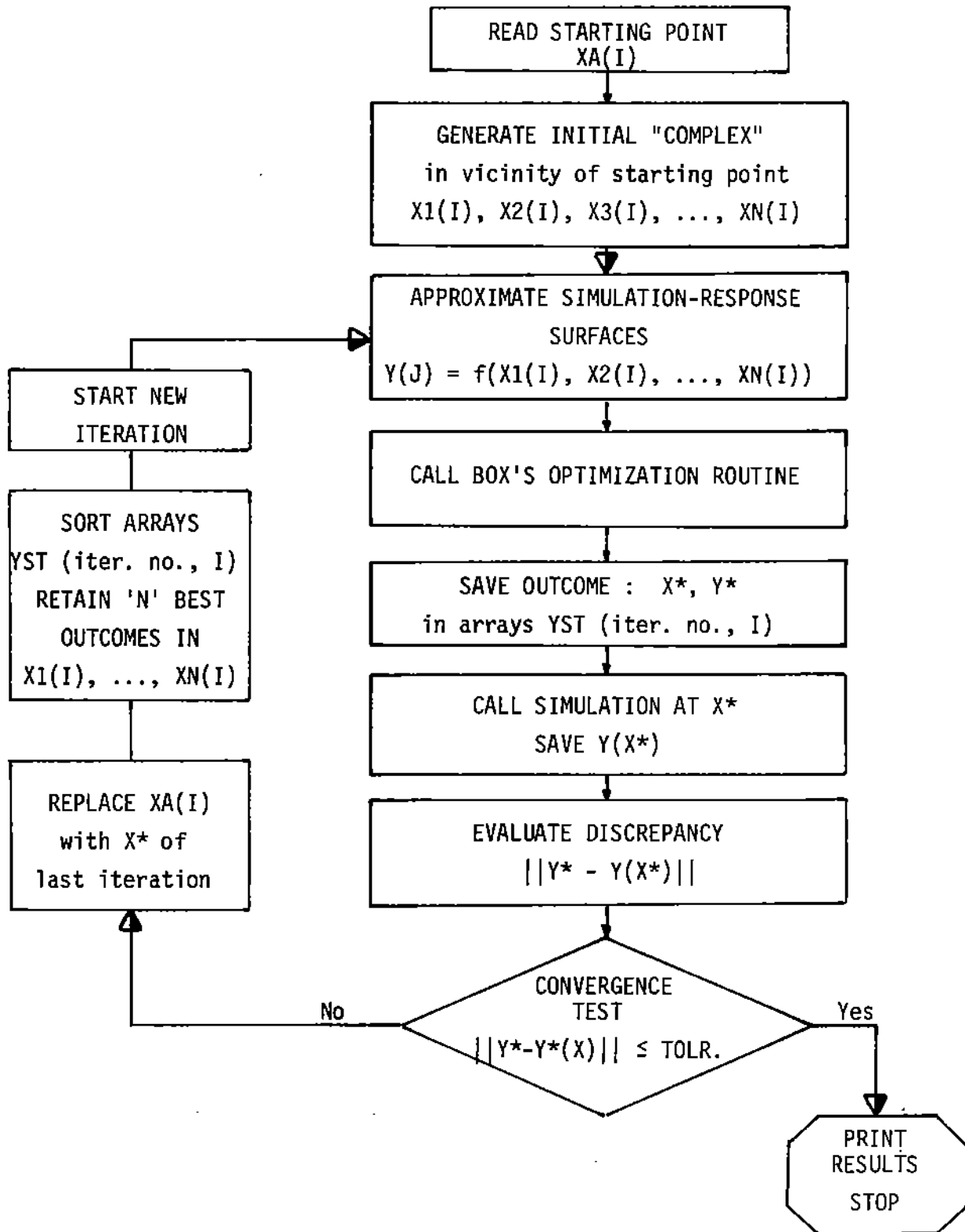


FIGURE 3.1 FLOWCHART OF ALGORITHM SBOPT

point repeats as worst point, the outcome of the latest iteration is always included in the set of retained points.

The above additional feature is believed to significantly accelerate the convergence of the algorithm. The convergence considerations are formally addressed in a later section. In the following section, the nature of and possible alternatives for the simulation approximation are discussed.

4. Simulation Approximation

Function approximation, commonly known as curve fitting techniques, have been developed in recent years, in an art in its own right. More and more sophisticated linear and non-linear regression techniques have been proposed, depicting trends and functional relationships between variables as observed by a wealth of experimental data. The situation described in the present report however, departs from the general case in that many successive approximations are foreseen, each based on a limited number of known points.

Since the operation is repetitive in nature in the proposed algorithm, a simple approximating scheme was sought, namely the one of linear regression. On the other hand, as was mentioned earlier, it appears logical to include in every successive approximation all additional information generated after each new iteration. However the above two arguments run against each other, as illustrated in Fig. 4.1. Indeed while a tangent to a curve (considered as a regression line) represents a very good approximation in the neighborhood of the point of tangence, a linear regression over a larger range of known points quickly becomes an unacceptable approximation. A trade-off is sought between the above two extreme possibilities, by adopting a straight-line approximation and accepting the burden of constraining the domain of its validity to an acceptable size.

Assuming that each simulation output Y_j is an independent function of all the input variables X_i , it can easily be seen that a linear regression requires a minimum of $(n+1)$ known points, where n is the dimension of the decision space

$$R^n = \{X_i : i = 1, \dots, n\} \quad (4-1)$$

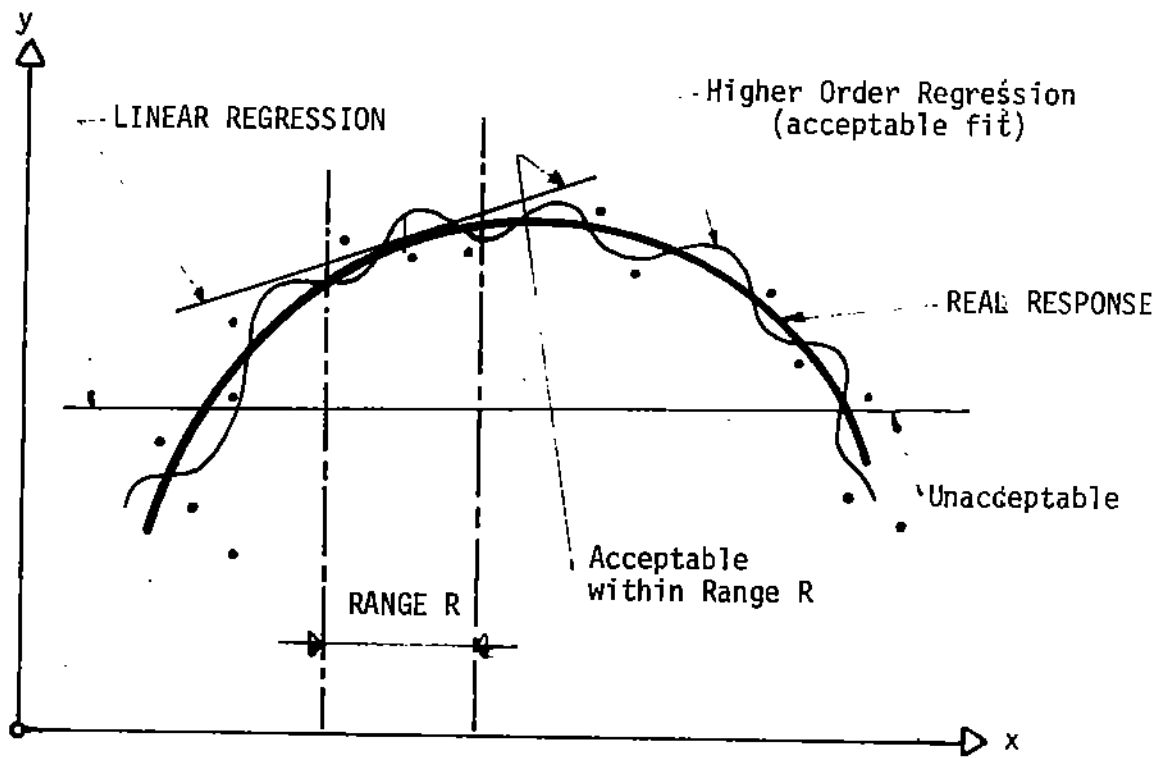


FIGURE 4.1 SIMULATION APPROXIMATION SCHEMES

Denoting by X_i^A, Y_j^A the coordinates of a known point A the linear approximation of Y_j can be written as

$$Y_j = Y_j^A + \alpha(X_1 - X_1^A) + \beta(X_2 - X_2^A) + \gamma(X_3 - X_3^A) + \dots + \eta(X_n - X_n^A) \quad (4-2)$$

where $\alpha, \beta, \gamma, \dots, \eta$ are the linear regression coefficients.

The determination of the 'n' regression coefficients requires the knowledge of an additional number of 'n' points. However care must be taken to avoid conditions of degeneracy. For example the (n+1) known points should be distinct, and better yet, uniformly distributed over the range of interest, so as to insure a small numerical error. The scheme of Eq. (4-2) is used in the algorithm SBOPT. The conditions of regularity are checked in the main-line routine, while the regression coefficients are determined in subroutine SIMAPRX. The listing of subroutine SIMAPRX is given in Appendix B. The following section deals with convergence considerations.

5. Convergence Considerations

The importance of the convergence considerations for an algorithm is very much a practical one. It constitutes a necessary condition for the algorithm to have any practical applicability. More important than the theoretical proof of convergence is the determination of the conditions required for a satisfactory rate of convergence. In this section, only a sketch of a proof is given, along with a list of necessary conditions for the existence and convergence of the solution.

The main feature of the iterative algorithm being the simulation approximation by regression hyperplanes, this algorithm reminds of the method of the secant encountered in classical numerical analysis. The obvious termination criterion is a tolerable discrepancy, at the solution point, between the approximated and the actual simulation response values. Moreover, the algorithm can be characterized as a fixed-point iterative scheme at the level of the simulation approximations, since the intermediary solution points are used to improve the approximations at the following step. A standard proof of convergence can be followed, for example, Wismer, 1971 (9).

However, the values of the independent variables X_i are determined at the intermediary steps of the algorithm such as to optimize the objective function while satisfying the set of constraints of the problem. Important assumptions will thus have to be made on the existence of such a solution. They include the requirement for convexity of the feasible space, and monotonicity or at least unimodality of the objective function within the feasible region.

While the above properties of convexity, and monotonicity or unimodality can be proved for the set of equations (2-1) and (2-3), they can

only be observed for the simulation response conditions (2-2). However, these properties define necessary conditions for the successive approximations to generate a stable solution. In particular, these approximations should not alter the convexity of the feasible space. In particular it is essential that the successive regressions do not degenerate. In a numerical example of the following section, an illustration of the instability resulting from degeneracy of the regression is shown.

Finally, an important consideration is that of the rate of convergence of the algorithm. Aside from the above mentioned properties and conditions, the rate of convergence also depends on the starting point. In the numerical experiment proposed in the following section convergence was achieved in 5-10 iterations.

6. Numerical Experiment

The example treated hereafter is inspired from an urban storm-drainage systems optimization scheme, reported in S. A. Dendrou, et al, (1978), (10). It is meant to provide a clear illustration of the implementation of the algorithm SBOPT.

An urban storm-drainage system can be defined, at the drainage basin level by three independent variables, denoted X_i , $i=1,3$, namely the detention storage capacity (volume), the contribution to a central treatment facility (rate) and a controlled overflow (rate). These measures are meant to alleviate the effects produced by storms and thundershowers. The effectiveness of the storm-drainage system can be monitored by such quantities as the quantity and quality of overflow, the frequency of street-flooding and others. These variables denoted by Y_j , $j=1,\dots,8$, are best generated by a digital model that processes a historical rainfall record and simulates the performance of the drainage system. The problem then consists of finding the least cost system configuration, while satisfying conditions on the acceptable pollution level and reliability of performance. The optimization problem equations are of the form

$$\text{Min}_{X_i} C = C(X_i, Y_j) \quad (6-1)$$

$$\text{s.t. } r_j : X_i \rightarrow Y_j \quad (6-2)$$

$$Y_j \leq t_{1j} \quad (6-3)$$

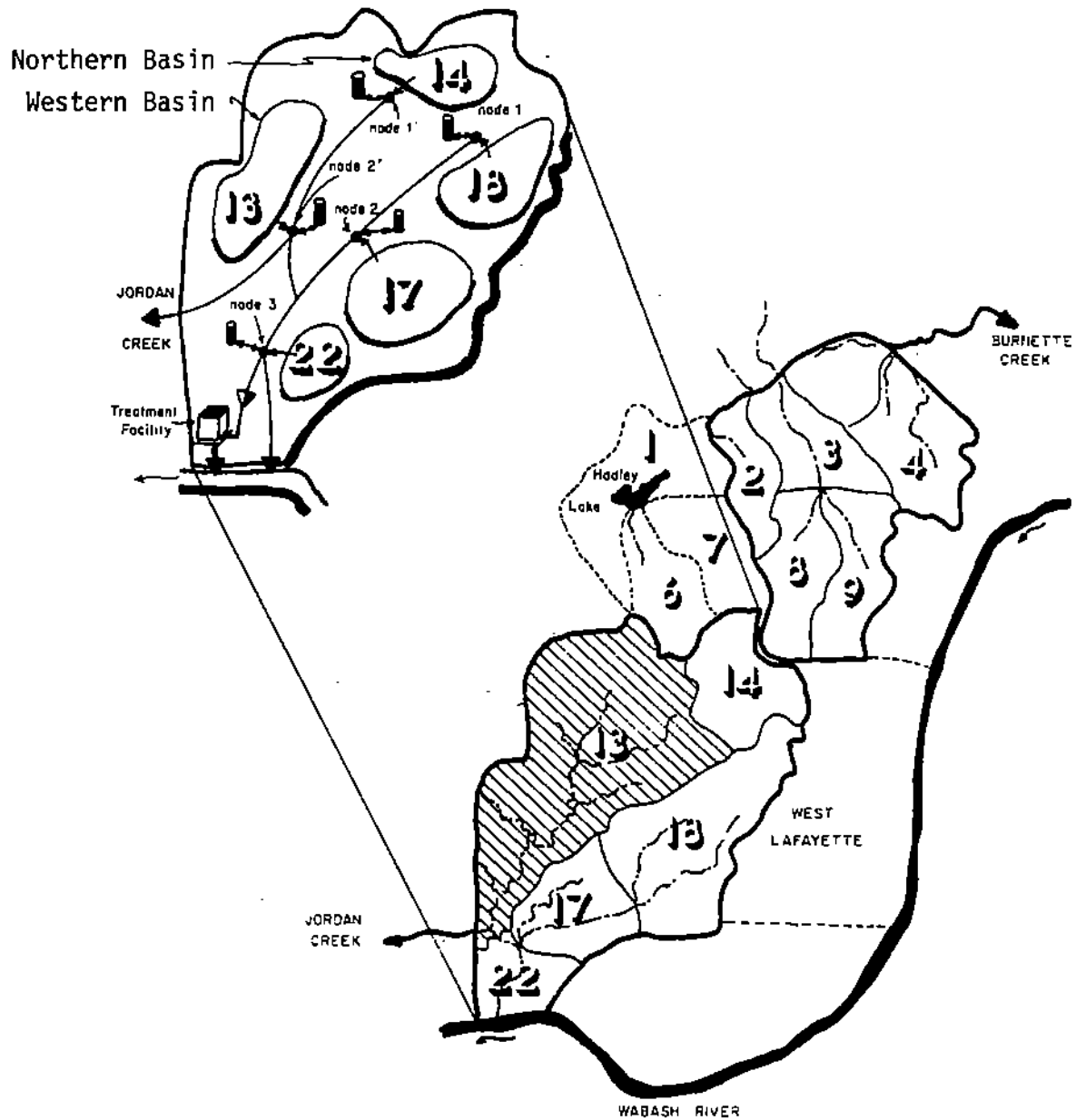


FIGURE 6.1 EXAMPLE OF A STORM-DRAINAGE SYSTEM

$$g_1(Y_j) \cdot \exp(g_2(Y_j)) \leq t_{2j} \quad (6-4)$$

$$[\theta_{ij}] \cdot [X_j] \leq t_{3i} \quad (6-5)$$

$$[\varepsilon_{ij}] \cdot [Y_j] \leq t_{4i} \quad (6-6)$$

$$h_1(X_i, Y_j) \cdot \exp(h_2(X_i, Y_j)) \leq t_5 \quad (6-7)$$

The simulation model used, Eq. (6-2), is the known hydrologic model STORM, (10).

The sets of runs are performed for two different drainage basins, the Northern and Western basins, Figure 6.1. First, the effect of instability by degeneracy of the regression scheme is illustrated in Figure 6.2. In the case of the upper figure, the regression scheme is allowed to consider redundant points among the set of regression points: Thus, the algorithm enters an unstable phase between iterations 5 and 15. When this possibility is eliminated, the algorithm proceeds to convergence in 5 steps.

In two other examples of application, respectively Figures 6.3 and 6.4, use is made of data from the Northern and Western basins, Figure 6.1. A slight oscillation is observed in both instances around the final value of convergence. This denotes that the boundary of the feasible region oscillates around a stable geometry for the successive simulation approximations (overshooting effect). Since the optimal point lies on the boundary, (see reference (10)), the above effect is repercutated on the values of the objective function.

The trajectory of the iterations for both the Northern and Western basins is shown in Table 6.1. In both cases it takes four iterations to converge to a solution within 5% of the acceptable response. This corresponds to eight (8) simulation calls altogether (four initial calls,

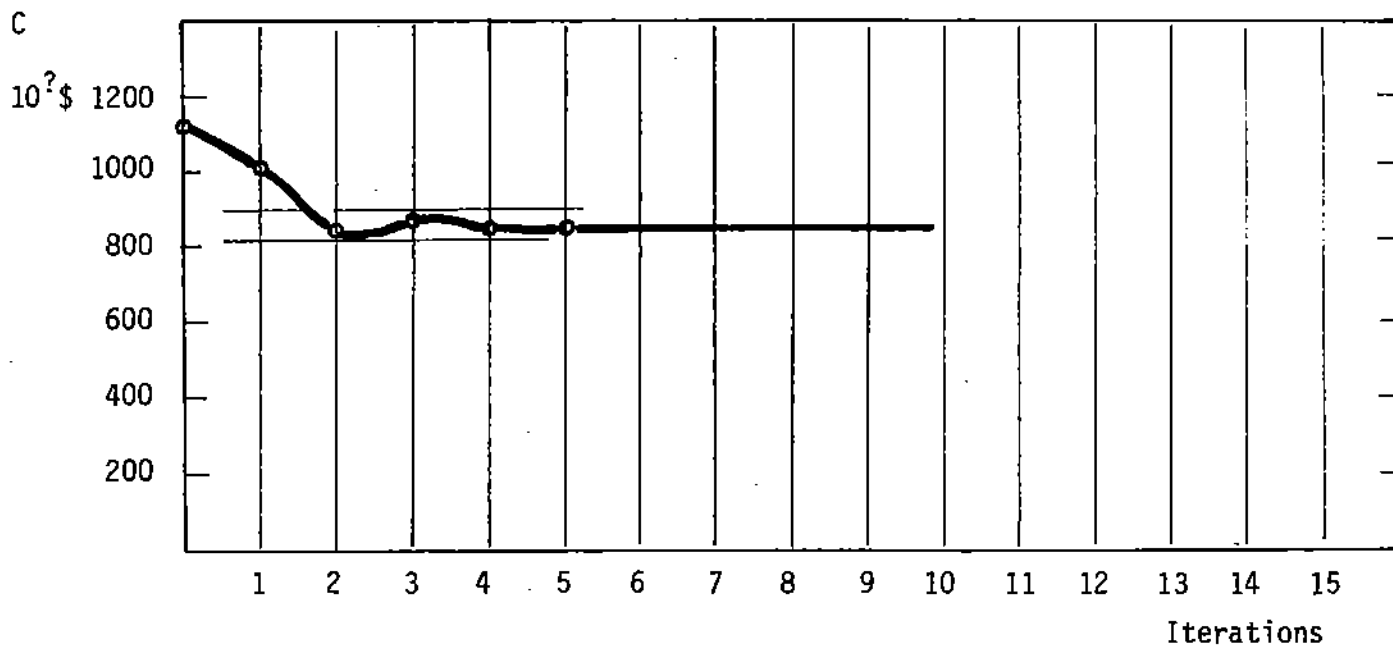
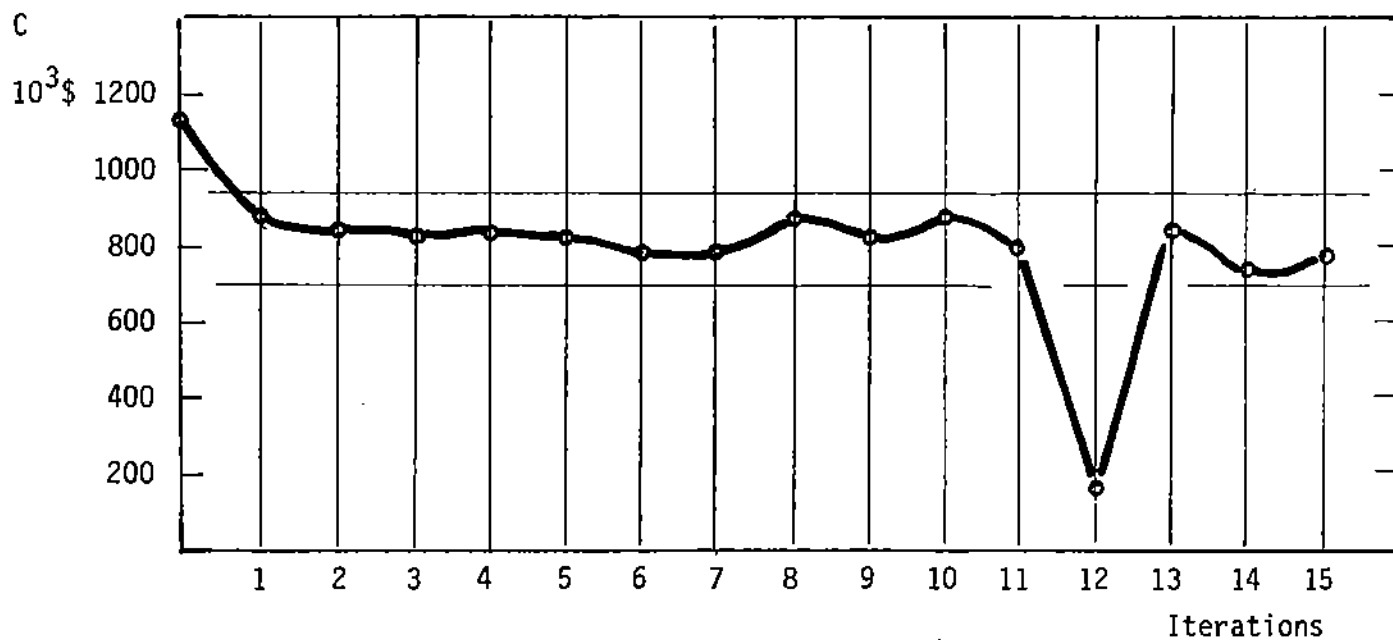


FIGURE 6.2 ILLUSTRATION OF INSTABILITY PRODUCED BY REGRESSION DEGENERATION

plus one per iteration). For comparison purposes, the "brutal force" approach used in (10), with the same starting point, requires 55 steps to convergence. Using an average of 10 simulation calls per step, this results in 550 simulation calls. The gain by the successive approximations method is thus seen to be appreciable.

The discrepancy between the approximated and the actual simulation response values in the first and last iterations for the case of the Northern basin is shown in Table 6.2. Often times the various simulation responses vary greatly in units and orders of magnitude. This is the reason for introducing the standard discrepancy as the r.m.s. of the actual discrepancies. Finally, in Table 6.3, the successive regression points and corresponding regression coefficients are shown for the case of the Northern basin.

In conclusion, more work has to be performed on the sensitivity of the model, as well as comparison with other techniques. One obvious direction of potential improvement is the approximation scheme for the response surfaces. For situations where the optimal point is expected to lie on the boundary of the feasible region it could be advantageous to approximate the simulation response using points on either side of the boundary and not in the feasible side alone.

TABLE 6.1 TRAJECTORIES OF ITERATIONS

	ITERATIONS	X1 (inches)	X2 (inches/hr)	X3 (inches/hr)	C $\times 10^3$ \$	DISCREPANCY	EXACT SOLUTION	STEPS TO CONVERGENCE (re.10)
NORTHERN BASSIN	0	0.250	0.040	0.010	629.		X1 = .237	55
	1	0.224	0.001	0.027	310.	4553.	X2 = .000	
	2	0.222	0.101	0.022	313.	253.	X3 = .010	
	3	0.227	0.001	0.010	301.	2304.		
	4	0.225	0.001	0.020	305.	69.	C = 328×10^3 \$	
WESTERN BASSIN	0	0.250	0.040	0.010	1057.			56
	1	0.232	0.001	0.005	619.	76.	X1 = .110	
	2	0.222	0.001	0.005	642.	64.	X2 = .001	
	3	0.224	0.001	0.005	638.	68.	X3 = .009	
	4	0.190	0.001	0.007	585.	43.	C = 509×10^3 \$	

TABLE 6.2 DISCREPANCY IN SIMULATION RESPONSE

SIMULATION RESPONSE	FIRST ITERATION			LAST ITERATION		
	Y^*	$Y(X^*)$	$Y^* - Y(X^*)$	Y^*	$Y(X^*)$	$Y^* - Y(X^*)$
Y_1	.614	.963	- .3483	.955	1.089	- .133
Y_2	.033	.103	- .0698	.102	.117	- .015
Y_3	.971	2.583	- 1.6118	2.582	2.631	- .048
Y_4	319.079	4773.141	-4454.0622	4788.8	4740.5	48.3
Y_5	68.055	578.097	- 510.0423	580.00	551.69	28.3
Y_6	44.819	819.579	- 774.7601	822.66	784.02	38.6
Y_7	2.665	186.270	- 183.6045	186.83	176.78	10.1
Y_8	1.546	50.256	- 48.7098	50.42	47.95	2.4

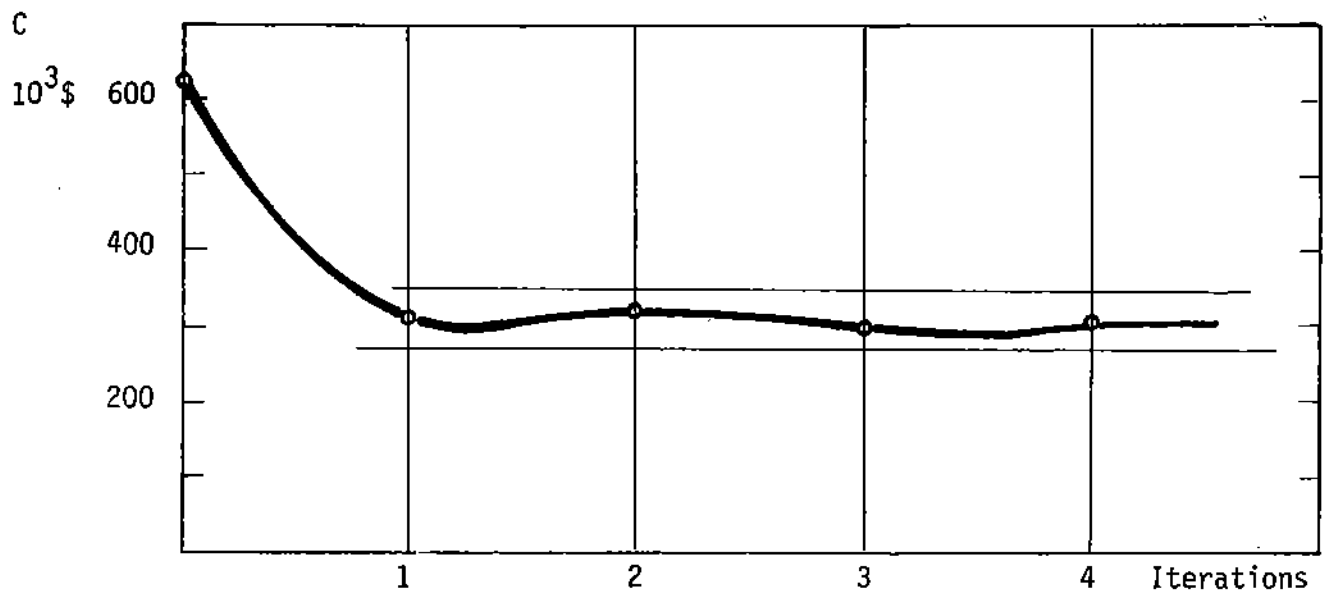


FIGURE 6.3 CONVERGENCE TRAJECTORY - NORTHERN BASIN

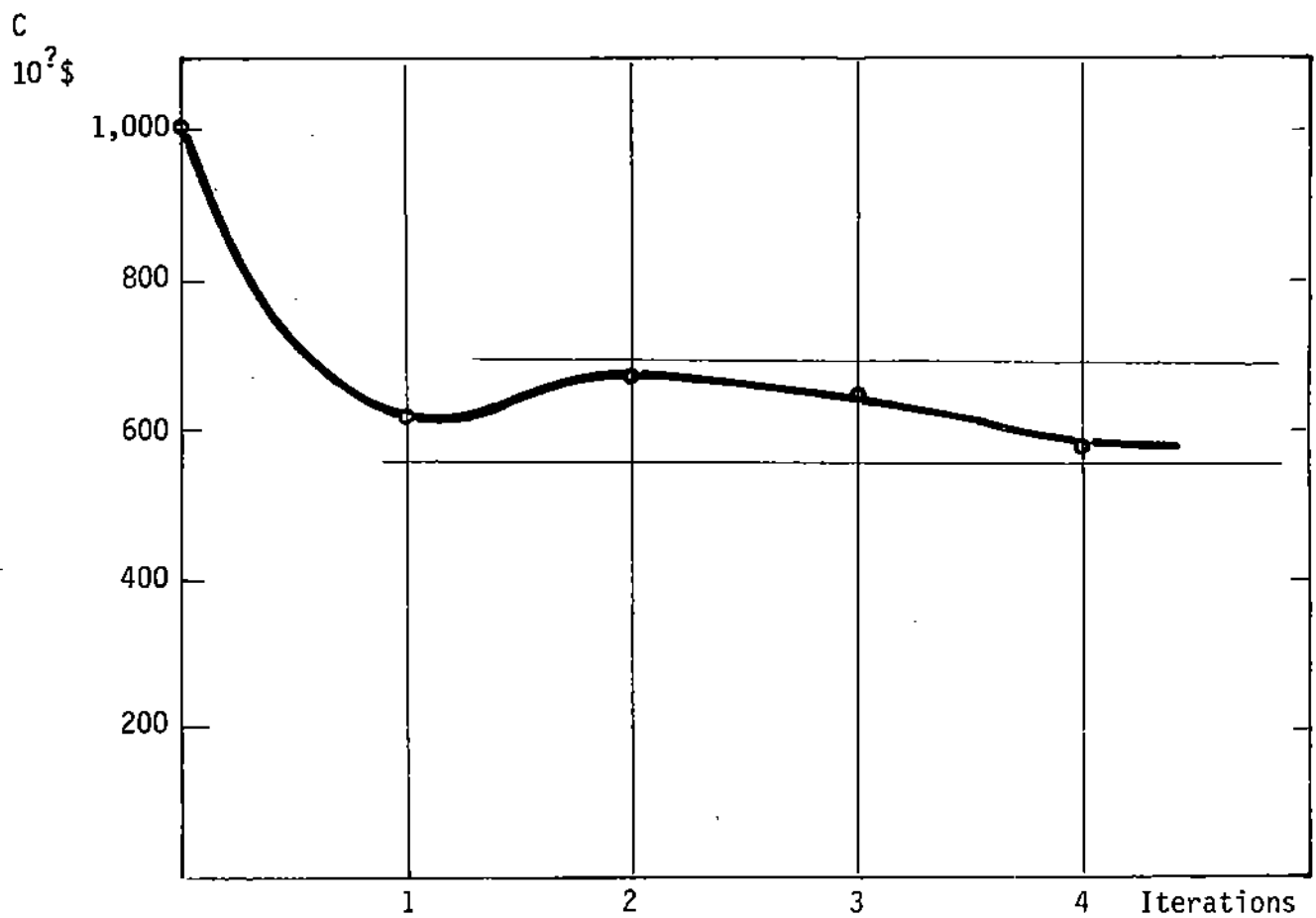


FIGURE 6.4 CONVERGENCE TRAJECTORY - WESTERN BASIN

TABLE 6.3 SUCCESSIVE SIMULATION APPROXIMATIONS

VARIABLES		REGRESSION POINTS				REGRESSION COEFFICIENTS		
		X1 _i	X2 _i	X3 _i	X4 _i	CALPH	CBETA	CGAMMA
	X ₁	.250	.400	.325	.287			
	X ₂	.040	.048	.025	.055			
	X ₃	.010	.012	.010	.008			
ITERATION 0	Y ₁	.477	.093	.324	.293	- 3.1669	6.9458	19.4282
	Y ₂	.046	.002	.031	.023	- .3384	.7667	.5211
	Y ₃	.545	.148	.381	.324	- 3.8281	11.3120	45.8211
	Y ₄	239.500	103.200	197.750	132.425	-1351.4863	5458.5424	15741.9355
	Y ₅	31.500	18.000	27.000	18.450	- 190.9247	934.6237	4064.5161
	Y ₆	31.500	14.400	26.750	18.037	- 181.2222	744.4444	2250.0000
	Y ₇	9.000	3.000	7.750	5.100	- 44.5305	129.3190	- 145.1613
	Y ₈	2.500	1.200	2.250	1.550	- 10.8053	38.4707	16.1290
	X ₁	.224	.400	.325	.287			
	X ₂	.001	.048	.025	.055			
	X ₃	.027	.012	.010	.008			
ITERATION 1	Y ₁	.963	.093	.324	.293	- 6.2668	6.0202	3.0880
	Y ₂	.103	.002	.031	.023	- .7406	.7770	.4758
	Y ₃	2.583	.148	.381	.324	- 18.9628	21.0244	4.9472
	Y ₄	4773.141	103.200	197.750	132.425	7488.9253	43473.9354	6019.9884
	Y ₅	578.097	18.00	27.000	18.450	-4507.6489	5255.7303	718.1408
	Y ₆	819.579	14.400	26.750	18.037	-6468.4881	7488.8467	959.7831
	Y ₇	186.270	3.000	7.750	5.100	-1467.7455	1695.9199	245.6747
	Y ₈	50.256	1.200	2.250	1.550	- 393.6508	456.3060	63.9253
	X ₁	.222	.400	.325	.287			
	X ₂	.001	.048	.025	.055			
	X ₃	.022	.012	.010	.008			
ITERATION 2	Y ₁	1.089	.093	.324	.293	- 7.2179	7.0769	4.4592
	Y ₂	.117	.002	.031	.023	- .8485	.8961	.6844
	Y ₃	2.631	.148	.381	.324	- 19.1505	21.1447	7.0419
	Y ₄	4540.543	103.200	197.750	132.425	5238.6595	40715.1759	8278.7999
	Y ₅	551.694	18.000	27.000	18.450	-4249.4982	4938.1576	989.6060
	Y ₆	784.019	14.400	26.750	18.037	-6116.1131	7054.2635	1323.9932
	Y ₇	176.779	3.000	7.750	5.100	-1376.6489	1584.4687	337.5366
	Y ₈	47.950	1.200	2.250	1.550	- 371.1159	428.5889	88.0955

List of References

1. Box, M. J., "A New Method of Constrained Optimization and a Comparison with Other Methods," Computer J., 8, 1965, pp. 42-52.
2. Farrell, W., McCall, C., and Russell, E., "Optimization Techniques for Computerized Simulation Models," Report to Office of Naval Research, NTIS #AD-A011 844/8G1, 1975.
3. Billes, W. E., "A Gradient-Regression Search Procedure for Simulation Experimentation," Proceedings of the 1974 Winter Simulation Conference, Vol. 2, pp. 491-497.
4. Smith, D. E., and Storck, C. E., "Research on an Optimizer Computer Program for Use in Simulation Studies," NTIS, (AD766-089/7WC), August 1973.
5. Smith, D. E., "An Empirical Investigation of Optimum-Seeking in the Computer Simulation Situation," Operations Research, Vol. 21, No. 2, March-April 1973, pp. 475-497.
6. Eldridge, D. L., "Experimental Optimization of Statistical Simulation," Proceedings of the 1974 Winter Simulation Conference, pp. 503-510.
7. Luss, R., and Jaakola, T. H. I., "Optimization by Direct Search and Systematic Reduction of the Size of the Search Region," American Institute of Chemical Engineers Journal, Vol. 19, No. 4, July 1973, pp. 760-766.
8. Kleijner, J. P. C., Naylor, T. H., and Seaks, T. G., "The Use of Multiple Ranking Procedures to Analyze Simulations of Management Systems: A Tutorial," Management Science, Vol. 18, February 1972, pp. B245-B257.
9. Wismer, D. A., Distributed Multilevel Systems, Chapter 6, pp. 252-253, "Optimization Methods for Large-Scale Systems ... with Applications," D. A. Wismer, Editor, McGraw-Hill, New York, 1971.
10. Dendrou, S. A., Talavage, J. J., and Delleur, J. W., "Urban Storm-Drainage Systems Planning," Technical Report No. 101, Purdue University Water Resources Research Center, May 1978.

APPENDIX A

```

SUBROUTINE SBOPT (N,M,K,ITMAX,ALPHA,BETA,GAMMA,DELTA,NIT,IEU2,NO,N A 10
IKOUNT,IPRINT) A 20
***** A 30
SIMULATION BASED OPTIMIZATION SCHEME A 40
----- A 50
FOR DETAILED DEFINITION OF VARIABLES SEE REF. 10/ A 60
TRANSFERED THROUGH COMMON-BLOCK FROM MAIN-LINE ROUTINE = A 70
S,T,ADR,AREA,LSUB,ICoord,TF,UF,OU,TO,OP A 80
DEFINITION OF VARIABLES A 90
----- A 100
G. LE. (X) . LE. H. THRESHOLD CONSTRAINTS A 110
X1,X2,X3,X4, XA=X1, = GIVEN REGRESSION POINTS A 120
CALPH,CBETA,CGAMMA, = REGRESSION COEFFICIENTS A 130
Y (.....) = ARRAY OF INTERMEDIARY RESULTS A 140
( UP TO 40 ITERATIONS ) A 150
YST(.....) = ACTUAL SIMULATION RESPONSE A 160
DYST(.....) = DISCRIPENCY A 170
DNST(.....) = STD. DISCRIPENCY A 180
DSORT(..) = SORTED ARRAY OF DNST A 190
----- A 200
COMMON /SAVE/ Y(40,18),YST(40,8),DYST(40,8),DNST(40),ITENO(40) A 210
COMMON /DNE/ X(5,76),R(5,3),F(5),G(76),H(76),XC(76),NOCRD,ITER1(15 A 220
1) A 230
COMMON /CNCTR/ CTHR(5) A 240
COMMON /APRXS/ XA(15),CALPH(8),CBETA(8),CGAMA(8) A 250
DIMENSION DSORT(40) A 260
COMMON /FORPP/ X1(15),X2(15),X3(15),X4(15),NPOINTS A 270
INTEGER GAMMA A 280
----- A 290
INITIALIZATION A 300
===== A 310
NPOINTS=1 A 320
NIT=1 A 330
DO 101 LIJ=1,M A 340
101 WRITE (NO,149) LIJ,G(LIJ),LIJ,H(LIJ) A 350
DO 102 IIL=1,M A 360
IF (G(IIL).EQ.H(IIL)) WRITE (NOCRD,150) G(IIL),IIL,LSUB A 370
102 CONTINUE A 380
TRANSFER OF POINT X1 A 390
X1(1)=S(LSUB) A 400
X1(2)=T(LSUB) A 410
X1(3)=AOR(LSUB) A 420
X1(4)=TF(LSUB) A 430
X1(5)=VF(LSUB) A 440
X1(6)=TO(LSUB) A 450
DO 103 IP=1,5 A 460
103 X1(6+IP)=OP(IP,LSUB) A 470
GENERATION OF POINTS X2,X3,X4 A 480
R(2,1)=1. A 490
R(2,2)=1. A 500
R(2,3)=-1. A 510
R(3,1)=0. A 520
R(3,2)=-1. A 530
R(3,3)=0. A 540

```

```

R(4,1)=-1.
R(4,2)=1.
R(4,3)=1.
R(5,1)=-1.
R(5,2)=0.
R(5,3)=0.
DDS=0.15
DDT=0.015
DDAR=0.002
RS=S(LSUB)+DDS
RT=T(LSUB)+0.5*DDT
RCT=RT+AOR(LSUB)+DDAR
SUBROUTINE KSTORM IS A SIMULATION ROUTINE
CALL KSTORM (RS,RT,RCT)
X2(1)=RS
X2(2)=RT
X2(3)=RCT-RT
X2(4)=TF(LSUB)
X2(5)=UF(LSUB)
X2(6)=TO(LSUB)
DO 104 IDI=1,5
104 X2(6+IDI)=(OP(IDI,LSUB))
RS=S(LSUB)+.5*DDS
RT=T(LSUB)-DDT
RCT=RT+AOR(LSUB)
IF (RT.LT.0.) RT=0.
CALL KSTORM (RS,RT,RCT)
X3(1)=RS
X3(2)=RT
X3(3)=RCT-RT
X3(4)=TF(LSUB)
X3(5)=UF(LSUB)
X3(6)=TO(LSUB)
DO 105 IDI=1,5
105 X3(6+IDI)=(OP(IDI,LSUB))
RS=S(LSUB)+DDS/4.
RT=T(LSUB)+DDT
RCT=RT+AOR(LSUB)-DDAR
IF (RCT.LT.0.) RCT=0.
CALL KSTORM (RS,RT,RCT)
X4(1)=RS
X4(2)=RT
X4(3)=RCT-RT
X4(4)=TF(LSUB)
X4(5)=UF(LSUB)
X4(6)=TO(LSUB)
DO 106 IDI=1,5
106 X4(6+IDI)=(OP(IDI,LSUB))
START MAIN LOOP OF SBOPT
*****
EVALUATION OF REGRESSION COEFFICIENTS
107 CALL SIMAPRX
X(1,1)=X1(1)
X(1,2)=X1(2)
X(1,3)=X1(3)
*COMPLEX* PACKAGE OF BOX, REF,(1), CONTAINS
SUBROUTINES= CONSX,CHECKK,CENTR,FUNC,CONST
CHECK FEASIBILITY OF STARTING POINT X1(.)
CALL CHECKK (N,M,K,NKOUNT,1,1,NO,DELTA,1,BETA)
CALL FUNC (N,M,K,1,NO,NKOUNT)

```

```

A 730
A 740
A 750
A 760
A 770
A 780
A 790
A 800
A 810
A 820
A 830
A 840
A 850
A 860
A 870
A 880
A 890
A 900
A 910
A 920
A 930
A 940
A 950
A 960
A 970
A 980
A 990
A 1000
A 1010
A 1020
A 1030
A 1040
A 1050
A 1060
A 1070
A 1080
A 1090
A 1100
A 1110
A 1120
A 1130
A 1140
A 1150
A 1160
A 1170
A 1180
A 1190
A 1200
A 1210
A 1220
A 1230
A 1240
A 1250
A 1260
A 1270
A 1280
A 1290
A 1300
A 1310
A 1320
A 1330
A 1340
A 1350
A 1360
A 1370
A 1380
A 1390
A 1400
A 1410
A 1420
A 1430
A 1440

```

```

DO 109 II=2,K
DO 108 J=1,N
108 X(II,J)=0.0
109 CONTINUE
C
C
C PERTURBATION GENERATED  $\neq$ COMPLEX $\neq$  REF.(1)
C
C
C DO 111 II=2,K
C I=II
C K1=II-1
C DO 110 J=1,N
C X(II,J)=X(1,J)+R(II,J)*DELTA*.93
110 CONTINUE
CALL CHECKK (N,M,K,NKOUNT,I,KODE,NO,DELTA,K1,BETA)
CALL FUNC (N,M,K,I,NO,NKOUNT)
111 CONTINUE
C
C
C CALL MAIN-LINE  $\neq$ COMPLEX $\neq$ - ROUTINE
C
C
C CALL CONSX (N,M,K,ITMAX,ALPHA,BETA,GAMMA,DELTA,IT,IEU2,NO,NKOUNT,I
1PRINT)
C
C
C SAVE SUBOPTIMAL POINT
C
C
C NAB=11+NTOT
C Y(NIT,4)=TF(LSUB)
C Y(NIT,5)=VF(LSUB)
C Y(NIT,6)=TO(LSUB)
C DO 112 IQ=1,5
112 Y(NIT,6+IQ)=OP(IQ,LSUB)
C DO 113 IW=1,N
C Y(NIT,IW)=X(IEU2,IW)
113 X1(IW)=X(IEU2,IW)
C
C
C
C RS=X1(1)
C RT=X1(2)
C RCT=RT+X1(3)
C
C
C CALL ACTUAL SIMULATION RESPONCE
C
C
C CALL KSTORM (RS,RT,RCT)
C
C
C
C YST(NIT,1)=TF(LSUB)
C YST(NIT,2)=VF(LSUB)
C YST(NIT,3)=TO(LSUB)
C DO 114 LI=1,5
114 YST(NIT,3+LI)=OP(LI,LSUB)
C INFL=0
C
C
C
C EVALUATE DISCRIPENCY
C
C
C
C DO 115 KK=1,8
C DYST(NIT,KK)=Y(NIT,3+KK)-YST(NIT,KK)
C ABA=ABS(DYST(NIT,KK))
C IF (YST(NIT,KK).GE.1.) ABET=BETA*YST(NIT,KK)
C
C
C
C CHECK CONVERGENCE
C
C
C IF (YST(NIT,KK).LE.1.) ABET=BETA
C IF (ABA.GE.ABET) INFL=10
115 CONTINUE
C DNST(NIT)=0.
C DO 116 KI=1,8
116 DNST(NIT)=DNST(NIT)+DYST(NIT,KI)**2
C DNST(NIT)=SQRT(DNST(NIT))
C
C

```

```

A 1450
A 1460
A 1470
A 1480
A 1490
A 1500
A 1510
A 1520
A 1530
A 1540
A 1550
A 1560
A 1570
A 1580
A 1590
A 1600
A 1610
A 1620
A 1630
A 1640
A 1650
A 1660
A 1670
A 1680
A 1690
A 1700
A 1710
A 1720
A 1730
A 1740
A 1750
A 1760
A 1770
A 1780
A 1790
A 1800
A 1810
A 1820
A 1830
A 1840
A 1850
A 1860
A 1870
A 1880
A 1890
A 1900
A 1910
A 1920
A 1930
A 1940
A 1950
A 1960
A 1970
A 1980
A 1990
A 2000
A 2010
A 2020
A 2030
A 2040
A 2050
A 2060
A 2070
A 2080
A 2090
A 2100
A 2110
A 2120
A 2130
A 2140
A 2150
A 2160

```



```

TEMPA1=DSORT(IA1)
DSORT(IA1)=DSORT(IMA1)
DSORT(IMA1)=TEMPA1
IA1=IA1-MA1
IF (IA1.GE.1) GO TO 125
126 JAI=JAI+1
IF (JAI.GT.KAI) GO TO 123
GO TO 124
127 CONTINUE
DO 129 LI=1,NONE
DO 128 JL1=1,NONE
C
C PRINT,=DNST(I),DSORT(I)=,JL1,DNST(JL1),DSORT(L1)
C
IF (DNST(JL1).EQ.DSORT(L1)) GO TO 129
128 CONTINUE
129 ITEND(L1)=JL1
C
C END OF SORTING - DETERMINE NEW POINTS X1,X2,X3,X4
C
KK1=ITEND(NONE)
KK2=ITEND(NONE-1)
KK3=ITEND(NONE-2)
DO 130 L=1,3
X2(L)=(Y(KK1,L))
X3(L)=(Y(KK2,L))
X4(L)=(Y(KK3,L))
130 CONTINUE
DO 131 LIK=1,8
X2(3+LIK)=(YST(KK1,LIK))
X3(3+LIK)=(YST(KK2,LIK))
X4(3+LIK)=(YST(KK3,LIK))
131 CONTINUE
NKI=3
132 L21=0
L31=0
L41=0
L32=0
L43=0
L32=0
L43=0
C
C CHECK REDUNDANCY OF X1,X2,X3,X4
C
DO 133 I3=1,3
IF (X3(I3).EQ.X2(I3)) L32=10
IF (X2(I3).EQ.X1(I3)) L21=10
IF (X3(I3).EQ.X1(I3)) L31=10
IF (X4(I3).EQ.X1(I3)) L41=10
IF (X4(I3).EQ.X3(I3)) L43=10
IF (X4(I3).EQ.X2(I3)) L42=10
133 CONTINUE
IF (L41.NE.10) GO TO 134
GO TO 140
134 IF (L31.NE.10) GO TO 135
GO TO 144
135 IF (L21.NE.10) GO TO 138
KNONE=NONE-NKI
IF (KNONE.LE.0) GO TO 147
KKI=ITEND(KNONE)
DO 136 L=1,3
136 X2(L)=Y(KKI,L)
DO 137 L=1,8
137 X2(3+L)=YST(KKI,L)
NKI=NKI+1
GO TO 132
138 IF (L43.NE.10) GO TO 139
GO TO 140
139 IF (L42.NE.10) GO TO 143
140 KNONE=NONE-NKI

```

A 2890
A 2900
A 2910
A 2920
A 2930
A 2940
A 2950
A 2960
A 2970
A 2980
A 2990
A 3000
A 3010
A 3020
A 3030
A 3040
A 3050
A 3060
A 3070
A 3080
A 3090
A 3100
A 3110
A 3120
A 3130
A 3140
A 3150
A 3160
A 3170
A 3180
A 3190
A 3200
A 3210
A 3220
A 3230
A 3240
A 3250
A 3260
A 3270
A 3280
A 3290
A 3300
A 3310
A 3320
A 3330
A 3340
A 3350
A 3360
A 3370
A 3380
A 3390
A 3400
A 3410
A 3420
A 3430
A 3440
A 3450
A 3460
A 3470
A 3480
A 3490
A 3500
A 3510
A 3520
A 3530
A 3540
A 3550
A 3560
A 3570
A 3580

APPENDIX B

```

      IF (KNONE.LE.0) GO TO 147
      KKI=ITEND(KNONE)
      DO 141 L=1,3
141  X4(L)=Y(KKI,L)
      DO 142 L=1,8
142  X4(3+L)=YST(KKI,L)
      NKI=NKI+1
      GO TO 132
143  IF (L32.NE.10) GO TO 147
144  KNONE=NONE-NKI
      IF (KNONE.LE.0) GO TO 147
      KKI=ITEND(KNONE)
      DO 145 L=1,3
145  X3(L)=Y(KKI,L)
      DO 146 L=1,8
146  X3(3+L)=YST(KKI,L)
      NKI=NKI+1
      GO TO 132
147  CONTINUE
      GO TO 107
148  WRITE (60,158) LSUB
      RETURN
C
149  FORMAT (/,5X,2HG(,I2,2H)=,F10.3,10X,2HH(,I2,2H)=,F10.3,/)
150  FORMAT (/,5X,22H CAUTION  G(I)=H(I) =,F10.3,4X,18H AT CONSTRAIN
      1T ,I3,14H , SUBBASIN ,I4,/)
151  FORMAT (///,5X, 15H ITERATION NO. ,I4, 37H STANDARD DISCRIPENCY
      1 DNST =,F10.5,/)
152  FORMAT (/,5X, 6H X(1)=,F10.3, 6H X(2)=,F10.3, 6H X(3)=,F10.3,//
      1/)
153  FORMAT (/,5X, 5HINDEX,2X,2X, SHY*(I),2X,2X,2X, SHY(X*),2X,2X, 1
      11H DELTA  Y ,/)
154  FORMAT (/,5X,2X,I1,2X,2X,F9.3,2X,F9.3,2X,F9.4,/)
155  FORMAT (///,5X,7(2X, 2HQ(,I1, 2H)=,F9.2,2X))
156  FORMAT (///,5X, 33HITERATIONS , FROM WORST TO BEST ;,/,10X,15(2X,I
      13,2X),)
157  FORMAT (///,5X, 33HCORESPONDING NORM(DISCRIPENCY) .,/,10X,10(F8.2
      1,2X),)
158  FORMAT (/,5X, 53H FAILED TO CONVERGE IN ITMAX ITERATIONS
      1 ,I4,/)
C
      END

```

```

A 3590
A 3600
A 3610
A 3620
A 3630
A 3640
A 3650
A 3660
A 3670
A 3680
A 3690
A 3700
A 3710
A 3720
A 3730
A 3740
A 3750
A 3760
A 3770
A 3780
A 3790
A 3800
A 3810
A 3820
A 3830
A 3840
A 3850
A 3860
A 3870
A 3880
A 3890
A 3900
A 3910
A 3920
A 3930
A 3940
A 3950
A 3960
A 3970
A 3980
A 3990
A 4000

```

C	SUBROUTINE SIMAPRX	B 10
C	*****	B 20
C	DETERMINES LINEAR REGRESSION COEFFICIENTS FOR SIMULATION	B 30
C	RESPONSE APPROXIMATION	B 40
C	-----	B 50
C	INPUT PARAMETERS	B 60
C	X1,X2,X3,X4 = GIVEN POINTS	B 70
C	XA=X1 = CENTAL POINT OF REGRESSION	B 80
C	OUTPUT PARAMETERS	B 90
C	CALPH,CBETA,CGAMA = REGRESSION COEFFICIENTS	B 100
C	-----	B 110
C	COMMON /FORPP/ X1(15),X2(15),X3(15),X4(15),NPOINTS	B 120
C	COMMON /APRXS/ XA(15),CALPH(8),CBETA(8),CGAMA(8)	B 130
C	DIMENSION DEDLT(12)	B 140
C	EQUIVALENCE (DEDLT(1),D1BA)	B 150
C	EQUIVALENCE (DEDLT(2),D2BA)	B 160
		B 170
		B 180
		B 190
		B 200
		B 210
		B 220
		B 230
		B 240
		B 250
		B 260
		B 270
		B 280
		B 290
		B 300

	EQUIVALENCE (DEDLT(3),D3BA)	B	310
	EQUIVALENCE (DEDLT(4),D1DA)	B	320
	EQUIVALENCE (DEDLT(5),D2DA)	B	330
	EQUIVALENCE (DEDLT(6),D3DA)	B	340
	EQUIVALENCE (DEDLT(7),D1CA)	B	350
	EQUIVALENCE (DEDLT(8),D2CA)	B	360
	EQUIVALENCE (DEDLT(9),D3CA)	B	370
	EQUIVALENCE (DEDLT(10),DYBA)	B	380
	EQUIVALENCE (DEDLT(11),DYCA)	B	390
	EQUIVALENCE (DEDLT(12),DYDA)	B	400
C		B	410
	DO 101 IL=1,11	B	420
101	XA(IL)=X1(IL)	B	430
	WRITE (60,105)	B	440
	DO 102 I=1,11	B	450
102	WRITE (60,106) I,XA(I),X1(I),X2(I),X3(I),X4(I)	B	460
	D1BA=X2(1)-X1(1)	B	470
	D1CA=X3(1)-X1(1)	B	480
	D2BA=X2(2)-X1(2)	B	490
	D2CA=X3(2)-X1(2)	B	500
	D3BA=X2(3)-X1(3)	B	510
	D3CA=X3(3)-X1(3)	B	520
	D1DA=X4(1)-X1(1)	B	530
	D2DA=X4(2)-X1(2)	B	540
	D3DA=X4(3)-X1(3)	B	550
	WRITE (60,107)	B	560
	DO 104 K=1,8	B	570
	DYBA=X2(K+3)-X1(3+K)	B	580
	DYCA=X3(3+K)-X1(3+K)	B	590
	DYDA=X4(3+K)-X1(3+K)	B	600
C		B	610
	DO 103 I=1,12	B	620
	IF ((DEDLT(I)).EQ.0.0000) DEDLT(I)=.0001	B	630
103	CONTINUE	B	640
C		B	650
	CGAMA(K)=(DYBA*D1BA*D1CA*D2DA+DYBA*D1CA*D1DA*D2BA-DYCA*D1BA*D1B	B	660
1	A*D2DA-DYCA*D1BA*D1DA*D2BA-DYBA*D1BA*D1DA*D2CA-DYBA*D1CA*D1DA*D	B	670
2	2BA+DYDA*D1BA*D1BA*D2CA+DYDA*D1CA*D1BA*D2BA)/(D1BA*D1BA*D2CA*D3	B	680
3	DA+D1BA*D1CA*D2BA*D3DA+D1DA*D1BA*D2CA*D3BA+D1CA*D1DA*D2BA*D3BA+	B	690
4	D1BA*D1BA*D2DA*D3CA+D1BA*D1DA*D2BA*D3CA+D2CA*D1BA*D2DA*D3BA+D1C	B	700
5	A*D1DA*D2BA*D3BA)	B	710
	CBETA(K)=(DYBA*D1DA-DYDA*D1BA-CGAMA(K))*(D1BA*D3DA+D1DA*D3BA)/(B	720
1	D1BA*D2DA+D1DA*D2BA)	B	730
	CALPH(K)=(DYBA-CBETA(K)*D2BA-CGAMA(K)*D3BA)/D1BA	B	740
	WRITE (60,108) K,CALPH(K),CBETA(K),CGAMA(K)	B	750
104	CONTINUE	B	760
	RETURN	B	770
C		B	780
105	FORMAT (///,12X, 1HI,15X, 5HX(I),7X, 5HX1(I),7X, 5HX2(I),7X,	B	790
	1 5HX3(I),7X, 5HX4(I),/)	B	800
106	FORMAT (/,10X,I4,10X,5(F12.3,3X),/)	B	810
107	FORMAT (//,9X, 5HINDEX,2X, 8HCALPH(I),3X, 8HCBETA(I),3X, 8HCGA	B	820
	1MA(I),//)	B	830
108	FORMAT (//,10X,I3,2X,F10.4,2X,F10.4,2X,F10.4,/)	B	840
C		B	850
	END	B	860

	SUBROUTINE LSTORM (X22)	C	10
	*****	C	20
	*****	C	30
	TRANSFERED THROUGH COMMON-BLOCK =	C	40
	S, T, AOR, AREA, LSUB, ICOORD, TF, UF, OU, TO, OP	C	50
	-----	C	60
		C	70
		C	80
		C	90
		C	100
	DIMENSION X22(76)	C	110
	COMMON /APRXS/ XA(15), CALPH(8), CBETA(8), CGAMA(8)	C	120
		C	130
	STORM SIMULATION RESPONSE APROXIMATION	C	140
		C	150
		C	160
	DO 101 KI=1,8	C	170
	X22(3+KI)=XA(3+KI)+CALPH(KI)*(X22(1)-XA(1))+CBETA(KI)*(X22(2)-X	C	180
	1 A(2))+CGAMA(KI)*(X22(3)-XA(3))	C	190
	101 CONTINUE	C	200
	TF(LSUB)=X22(4)	C	210
	UF(LSUB)=X22(5)	C	220
	TO(LSUB)=X22(6)	C	230
	DO 102 LM=1,5	C	240
	102 DP(LM,LSUB)=X22(6+LM)	C	250
	RETURN	C	260
		C	270
	END	C	280