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Design of Water Distribution Networks Using Scattered Search: A Case Study

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ABSTRACT: Water distribution networks are one of the most important infrastructures in urban areas. As design and management of these networks include many components and issues, there are a variety of methods and models that could be considered as design and operating tools. These methods should be capable of considering the complexity and nonlinearities in simulation and optimization of water distribution networks. Among optimization methods, GA algorithms are widely applied in the optimization of water distribution networks because of their flexibility. However recently a new evolutionary algorithm has been emerged called Scatter Search (SS). The application of this model in different scientific fields has shown the high ability of this method. The greatest advantage of the SS method over GA is its higher speed in achieving the optimal solution. In this paper the application of GA and SS to water distribution networks are evaluated.

Keywords: Scatter Search, Optimization Algorithm, Water Distribution Network, Genetic Algorithm.

INTRODUCTION

The performance of water distribution networks highly affects the performance of other sectors in an urban area. The performance of water distribution networks is highly dependent on their design which should be optimized considering their different elements. There are many elements in each water distribution network for water delivery which are widely scattered throughout the system. The optimal design of the water distribution networks could considerably decrease the capital investment of network development.

Different optimization techniques are used for the design of water distribution networks such as linear programming (Jowitt and Germanopoulos, 1992), nonlinear programming (Chase and Ormsbee, 1993), dynamic programming (Lansey and Awumah, 1994), fuzzy logic (Angel *et al.*, 1999) and genetic algorithms (Savic *et al.*, 1997; Gupta *et al.*, 1999, van Zyl *et al.*, 2004). Most of these techniques have limitations and some simplifications are necessary. Sometimes these simplifications affect the optimal solution and introduce errors in using them in operation and simulation of the system. Some new optimization algorithms introduced in recent years such as different types of GA, require less simplification. Different improvements are made on GA algorithms such as messy GA (Halhal *et al.*, 19997), hybrid GA (van Zyl *et al.*, 2C04) and variable length GA (Kerachian and Karamouz, 2007). But as these techniques are based on random events, it may take considerable time to search the decision space and find a global optimal solution.

SS is an evolutionary optimization algorithm introduced by Glover (1977). It has been used in different fields such as unconstrained optimization, multi-objective assignment, optimizing simulation and mixed integer programming. The results of these studies have demonstrated the practical advantages of this approach over other evolutionary algorithms for solving different types of optimization problems.

In this paper the SS and GA algorithms have been applied to the optimal design of a sample and a real water distribution network. The objective function is to minimize the cost of the network development with constraints to provide reliable supply of adequate water with desired pressure in all the demand nodes.

In the next section, the structure of the optimization model has been described. In the following section the application of SS and GA to two-loop network example and Chahar-Dangeh water distribution network in Iran are evaluated. Finally a summary and conclusion is given.

OPTIMIZATION MODEL STRUCTURE

The water distribution network design problem considered in this paper involves minimizing the network construction costs subject to meeting minimum allowable pressure constraints under design demand levels in all demand nodes. As most of the water distribution development costs are related to piping, so the construction costs have been considered equal to the cost of pipes and their installation in the network. The decision variables of the model are the diameter of the water distribution network pipes.

The minimum pressure requirement at each demand node is implemented in the optimization model as a so called "soft" constraint. So when a solution violates the pressure requirement constraint, its fitness is heavily penalized but not removed from the potential optimal solutions. This approach is used, for large and real problems, because a feasible solution is unlikely to be reached in the initial stages of the optimization.

SCATTER SEARCH ALGORITHM

The Scatter Search (SS) process is built on the principles that underlie the surrogate constraint design. It is organized to (1) capture information that are not available separately in the original vectors; (2) take advantage of auxiliary heuristic solution methods to evaluate the combinations produced and to generate new vectors (Glover, 1997).

Scatter Search in contrast with other evolutionary procedures such as genetic algorithms provides unifying principles for joining solutions based on generalized path constructions (in both Euclidean and neighborhood spaces). It utilizes the strategic designs where other approaches resort to random search. Additional advantages are provided by drawing the adaptive memory on the foundations that link Scatter Search to Tabu Search (Glover *et al.*, 1999). Four basic methods of SS proposed by Laguna and Martí (2004) are extended in this study as presented in Figure 1. These elements are discussed briefly as follows:

The Diversification Generation Method (DGM)

This method is used for producing a set of trial vector solutions through heuristic processes designed for the problem considered. The produced solutions are scattered throughout the solution space as much as possible. This initial set of solutions is called P set. A particular mechanism in DGM prevents duplication of solutions in the P set. In the generated P set which is a large set of diverse vector solutions, each solution consists of decision variables of the optimization problem (here the diameter of each pipe).

The Reference Set Update Method (RSUM)

In this method, a subset of the best vectors is designated to be reference solutions. The reference set is the main element in SS that consists of "desirable solution" vectors according to both the "quality" of the objective function and "diversity" of the solution.

RSUM must reset the reference set in each iteration by monitoring the quality and diversity of trial solutions that are produced by the DGM or solution combination method. The size of reference set should be kept as short as possible, typically less than 20 solutions (Laguna *et al.*, 1999). If the size of the reference set becomes more than 20, it will be difficult to deal and needs considerable computational effort.

The Subset Generation Method (SGM)

This method provides subsets from the reference set that must be combined in order to produce new trial solutions using the solution combination method. For instance it can provide all or selected pairs of the reference set. The pairs could be selected by random number production.

The Solution Combination Method (SCM)

The subsets provided by SGM are combined linearly through this method in order to produce new solutions. These linear combinations are arranged to produce solutions both inside and outside the convex regions spanned by the reference solutions. Each subset can generate more than one new solution. This method is similar to the cross over function in the GA algorithm but SCM is not limited by the number of members that can participate in producing new solutions (just two parents in GA), number of produced solutions after combination (just two children in GA) and the way that pairs of solutions are combined. This loop is repeated until reaching the model termination criteria which can be a pre-specified iteration limit or when the objective function approaches a constant value.

These 4 methods form the general structure of the SS algorithm even though they might be used in different forms. There is an extra method, called the Improvement Method (IM) in the SS algorithm. This is not an essential method but is used in some studies for increasing the convergence rate of optimization problems. (Martí *et al.*, 2006).

THE ADOPTED SS ALGORITHM FOR WATER DISTRIBUTION NETWORKS

The size of the P set has been considered equal to 200 in this study. The initial reference set is built using

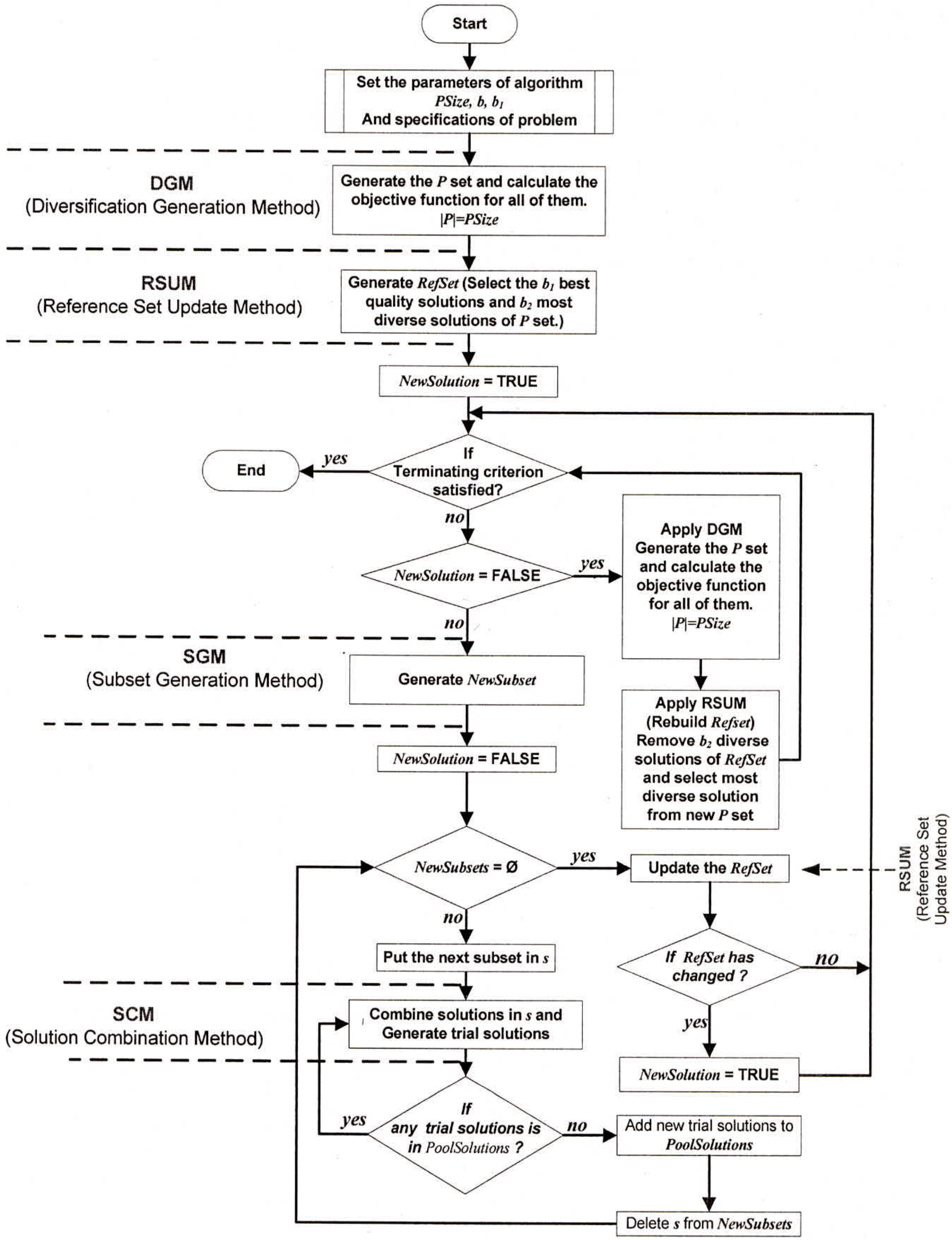

Fig. 1: The proposed algorithm of SS

RSUM. The size of the reference set (b) is considered to be equal to 10 and the amount of the best quality (b1) and most diverse (b2) solutions are considered to be equal to 5. After selecting the b1 solutions with the best quality from the P set, it is desirable to maximize the minimum distance between the solutions in the reference set to achieve the maximum diversity. For each remaining solution $\vec{x}$ in the P set and solution $\vec{y}$ in the reference set, a measure of distance or dissimilarity $d(\vec{x}, \vec{y})$ is calculated. The solution that maximizes $d_{\min}(\vec{x})$ is added to the reference set as follows (Laguna and Martí, 2004),

$$d_{\min}(\vec{x}) = \min_{\vec{y} \in \text{ Reference set}} \{ d(\vec{x}, \vec{y}) \}. \quad \dots (1)$$

Then the solution vectors in the reference set are sorted based on their objective function. After these two steps the iteration procedure of the algorithm begins. SGM generates subsets of the reference set and prepares them for SCM. The simplest form has been considered in this paper as all of the pairs of available solutions have been considered for subset generation which results in b(b–1)/2 number of subsets. By combining the subsets, four new solutions are generated as follows,

$$\begin{array}{ll} \vec{c}_1 = \vec{x}_1 + \vec{d} & \vec{c}_2 = \vec{x}_1 - \vec{d} \\ \vec{c}_3 = \vec{x}_2 + \vec{d} & \vec{c}_4 = \vec{x}_2 - \vec{d} \end{array} \quad \dots (2)$$

where each element of vector $\vec{d}$ (d_i) is calculated as follows,

$$d_i = \text{int}\left(\frac{|x_{1i} - x_{2i}| + 1}{2} \times r^*\right) \quad \dots (3)$$

where r^* is a uniform random number.

The amount of the objective function is calculated for all of the new generated solutions. Then the reference set is updated using RSUM according to new trial solution vectors and current reference set solutions. If the reference set changes, it means that there are new solutions that could join the reference set and the algorithm continues running. If the reference set does not change in two continuous steps, the diverse solutions are extracted from the reference set and DGM is repeated to produce a new P set and the new diverse solutions are selected from it. This procedure is called *"Reference Set Rebuilding"* (Martí *et al.*, 2006).

In each iteration, the termination criterions are checked. There are 2 terminating criterions considered in this study including: (1) maximum number of hydraulic simulation of the water distribution network and (2) achieving a specific amount of objective functions.

TWO-LOOP NETWORK EXAMPLE

A hypothetical water distribution network has been introduced by Alperovits and Shamir (1977) and is subsequently used by many others in different applications as a bench mark problem. This two-loop network consists of 8 pipes which are fed by a 210 m fixed head. Figure 2 shows the layout of this network.

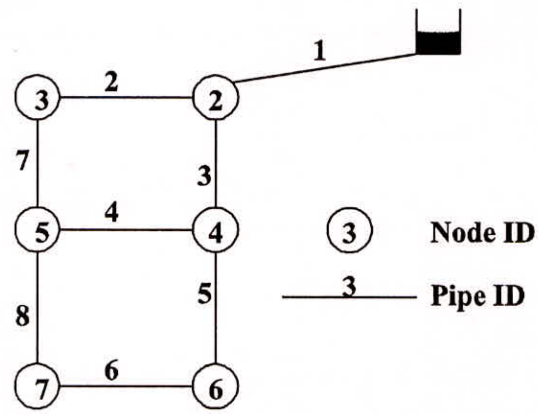

Fig. 2: The layout of the two-loop network (after Alperovits and Shamir, 1977)

All of the pipes have a fixed length and the Hazen-Williams coefficient equal to 1000 m and 130, respectively. The minimum acceptable pressure in all of the demand nodes (nodes 2 to 7) is selected as 30 m above ground level. The elevation and demand of nodes 2 to 7 are presented in Table 1. The diameter of the network pipes can be selected among the 14 available pipe diameters ranging from 25.4 mm to 609.6 mm (Table 2). The cost of each pipe size is given in Table 2.

Both of the proposed SS and GA algorithms are applied to the two-loop example network. The population size of the GA model is 200 and cross over and mutation probabilities are equal to 0.8 and 0.05, respectively. The results of SS and GA algorithm converge to the \$420,000 cost unit which is the same as Savic and Walters (1997). This solution satisfies the demand and pressure requirements of water delivery and therefore yields a zero head deficit. The average results of 100 runs of SS and GA algorithms are presented in Figure 3. This figure illustrates that SS has much a faster convergence rate compared to GA.

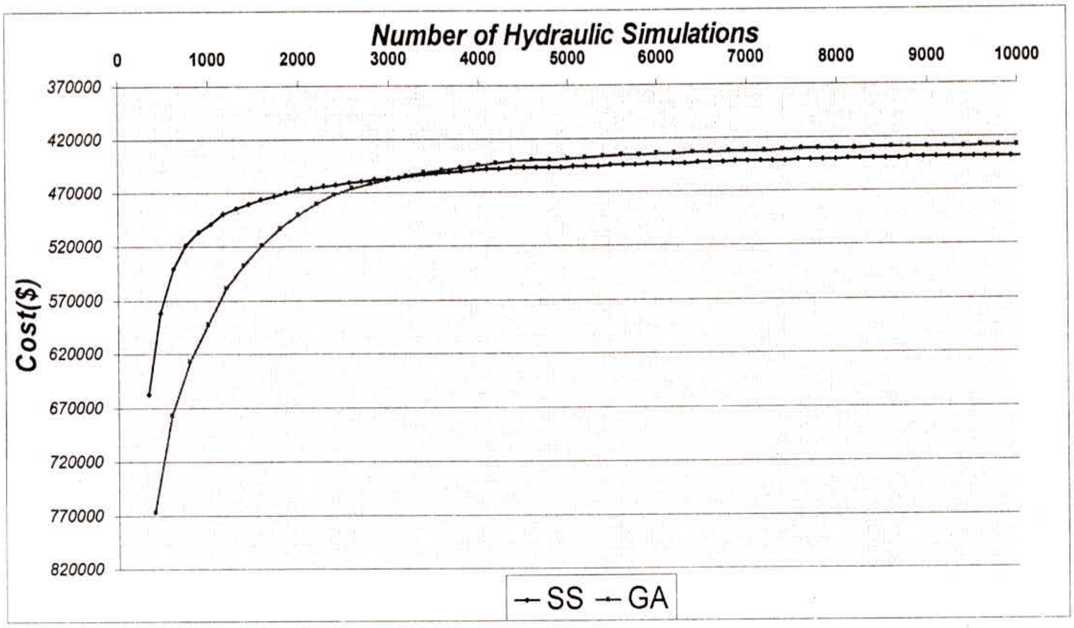

Fig. 3: The comparison between the average result of GA and SS in 100 runs

Table 1: The Nodal Characteristics of the Two-Loop Network

Node ID.	*Ground Level (m)*	*Demand (lit/s)*
1.	210.0	0 (Reservoir)
2.	150.0	27.78
3.	160.0	27.78
4.	155.0	33.33
5.	150.0	75.00
6.	165.0	91.67
7.	160.0	55.56

Table 2: Available Pipe Sizes and Assumed Costs

Diameter (mm)	*Unit Cost (US$/m)*	*Diameter (mm)*	*Unit Cost (US$/m)*
25.4	2	304.8	50
50.8	5	355.6	60
76.2	8	406.4	90
101.6	11	457.2	130
152.4	16	508	170
203.2	23	558.8	300
254	32	609.6	550

CHAHAR-DANGEH WATER DISTRIBUTION NETWORK DESIGN

Chahar-Dangeh is a small city located near Tehran, the capital of Iran. It supplies water to about 200000 residents where the water consumption per capita per day is equal to 170 liters. The layout of the Chahar-Dangeh water distribution network is illustrated in Figure 4. This is a complicated water distribution network and the optimization of its design requires considerable computational effort. The water demand at nodes included in this water distribution network are presented in Tables 3. All of the pipes assumed to have a fixed Hazen-Williams coefficient equal to 130. The costs given in Table 2, have also been used in this problem. The network is fed by a 1131.9 m fixed head.

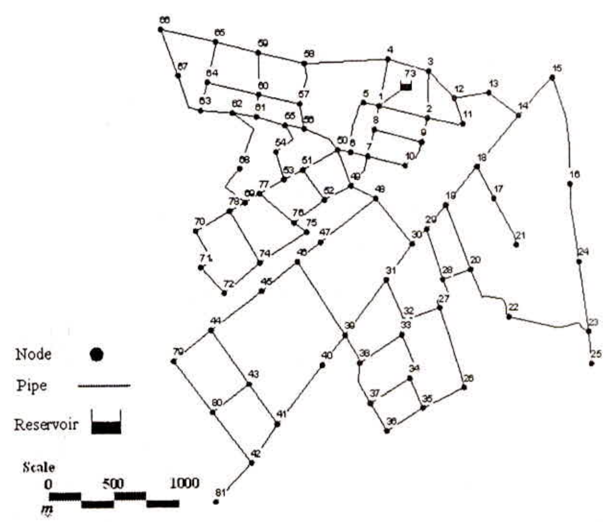

Fig. 4: The layout of Chahar-Dangeh water distribution network

The GA and SS algorithms with the same structures to the pervious example have been applied to the Chahar-Dangeh water distribution network. The results of these algorithms are presented in Figures 5 and 6. Both of the algorithms have found the same solution

Table 3: The Characteristics of Nodes in Chahar-Dangeh Water Distribution Network

Node ID	*Ground Level (m)*	*Demand (lit/s)*	*Node ID*	*Ground Level (m)*	*Demand (lit/s)*
1.	1097.9	0.95	41	1084.6	5
2.	1096.2	3.53	42	1082.7	12.36
3.	1097.1	0.28	43	1084.7	1.06
4.	1098.9	0.63	44	1087.6	1.06
5.	1098.1	1.37	45	1088.7	1.4
6.	1096.1	1.79	46	1090.2	1
7.	1095.2	2.54	47	1090.8	1.17
8.	1097	5.02	48	1094.5	1.4
9.	1094.6	3.4	49	1094.2	2.32
10.	1093.7	1.87	50	1096.1	8.31
11.	1096.3	0.28	51	1095.1	7.49
12.	1096.7	0.51	52	1093	7.71
13.	1096.9	0.4	53	1095.4	9.12
14.	1095.1	5.75	54	1097.5	7.29
15.	1096.1	1.14	55	1098.2	7.28
16.	1091.2	2.07	56	1097.5	4.36
17.	1090.1	12.86	57	1098.2	3.39
18.	1093.9	7.7	58	1100.3	0.95
19.	1092.4	11.01	59	1101.9	0.61
20.	1087.9	19.84	60	1099.6	3.49
21.	1087.9	8.12	61	1099	2.97
22.	1085.5	8.5	62	1098.7	1.44
23.	1083.9	1.66	63	1099	1.3
24.	1087.2	0.96	64	1100.3	0.77
25.	1081.9	0.77	65	1102.4	1.38
26.	1083.4	9.56	66	1102.5	10.9
27.	1086.4	15.85	67	1101	20.78
28.	1088.3	9.38	68	1095.4	1.3
29.	1091.8	4.86	69	1093.8	3.2
30.	1091.2	14.67	70	1093	21.06
31.	1089.7	2.03	71	1091	22.54
32.	1086.5	5.57	72	1088.4	1.32
33.	1085.9	2.49	74	1089.1	1.6
34.	1084.6	4.12	75	1091.9	1.6
35.	1082.6	3.69	76	1092.4	3.19
36.	1082.7	2.61	77	1094.2	3.19
37.	1083.9	2.77	78	1093.2	3.2
38.	1085.8	1.25	79	1087.6	1.56
39.	1088.2	2.51	80	1084.7	2.07
40.	1086.5	2.33	81	1082.7	21.1

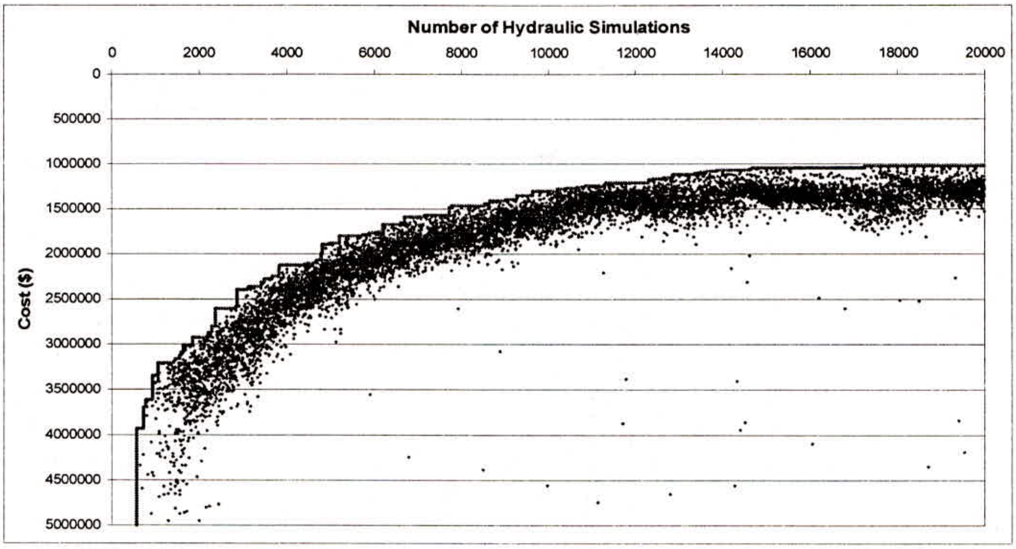

Fig. 5: Convergence of GA algorithm for Chahar-Dangeh water distribution network

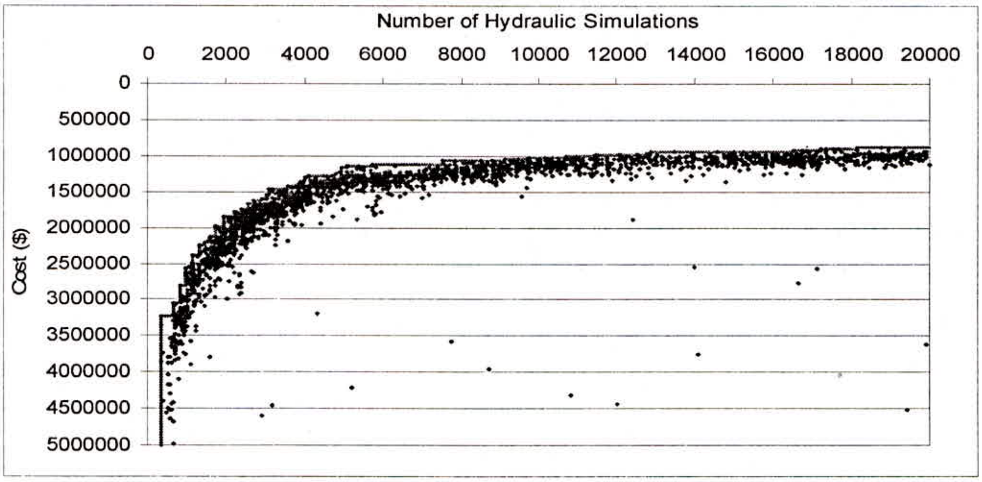

Fig. 6: Convergence of SS algorithm for Chahar-Dangeh water distribution network

with a cost of one million US Dollars. SS algorithm has found the optimal solution almost after 9000 hydraulic simulations. The optimal solution is found after 15000 hydraulic simulations with GA. This means that the SS algorithm has considerably less run time and computation effort. As can be seen in the GA algorithm the solutions are distributed around the optimal solution but the SS results are more scattered. This means that SS has searched the feasible solution space more and tested most of the possible solutions. This prevents the algorithm from getting trapped in the local optimal solutions.

SUMMARY AND CONCLUSION

The optimal design of water distribution networks is an important issue in integrated urban water management as it can save considerable amounts of money. There are different methods used for the optimal design of these networks. A popular method is GA. Although this method has shown good performance in producing an optimal solution in the design of water distribution network, it is very time consuming with possibility of getting trapped in the local solutions. In this paper a new evolutionary algorithm called the Scatter Search (SS) has been used for the optimal design of a water distribution network. This algorithm is more flexible than GA and has performed better than GA in many respects.

The results of this study showed that the convergence rate of the SS model especially in the first 2000 iterations is considerably more than the GA model. The application of SS to a real water distribution network showed that it converges to the optimal solution in about half time compared to GA to find the optimal solution. This is important in the design of large scale systems. Another advantage of SS is that it searches the feasible solutions guardedly. This prevents finding the local optimal solutions which is common problem in GA model. The performance of SS can be further improved by extending the SCM and SGM methods to include improvement method.

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