Scientia Iranica, Vol. 13, No. 3, pp 234–244
© Sharif University of Technology, July 2006

SCIENTIA
IRANICA

Application of a Genetic Algorithm to Storm Sewer Network Optimization

M.H. Afshar[1]

In this paper, a genetic algorithm is developed for the optimal design of storm water networks. The nodal elevations of the sewer network are taken as the decision variables. A steady state simulation code is used to analyze the trial solutions provided by the GA optimizer. The performance of the four selection schemes namely, conventional roulette wheel, roulette wheel selection with linear scaling, roulette wheel selection with ranking and, finally, roulette wheel selection with power law scaling, is studied by applying the model to some benchmark examples in the literature. The conventional roulette wheel selection scheme produced superior results compared to other methods. The results produced by the proposed model are either comparable or superior to existing results in the literature.

INTRODUCTION

Storm water networks are an essential part of the infrastructure of any society. Construction and maintenance of these large scale networks require a huge amount of investment. Any reduction of total cost in the construction of these networks through proper design would result in considerable savings. Pipes and excavations constitute the main cost of storm water networks, but, reducing the cost of excavations and pipes often creates contradictory objectives in the design of storm water networks. Any reduction in pipe size, under the usual constraints of minimum and maximum velocities, requires an increase in the pipe slope leading to more excavation costs. Reducing the excavation costs, on the other hand, requires milder slopes for the pipe, leading to bigger pipe sizes to carry the design discharge. Any economical design of storm water networks, therefore, requires an optimal trade-off between the pipes and excavation costs, which cannot be achieved by engineering judgments.

An optimal design for storm sewer networks has, therefore, received considerable attention in the past decades. Existing attempts for optimization of storm water networks can be categorized into three groups. Dynamic Programming (DP) methods are the first and most used method for the optimal design of storm sewer networks, due to the serial features of these networks. Robinson and Labadie [1], Yen et al. [2], Kulkarni and Khanna [3] and Li et al. [4] employed DP to optimally design storm water networks. Dynamic programming methods, which are theoretically capable of finding the global optimum solution, suffer from the so-called curse of dimensionality and, therefore, are not applicable to real-world sewer networks. There have been some attempts, using the linear programming method, to solve the problem of storm water design. Elimam et al. [5] used a combination of Linear Programming (LP) and a heuristic approach to design a large scale storm water network. Heuristic approaches are recently being used for the problem, due to their simplicity and the good results achieved. Miles and Heaney [6] and Afshar and Zamani [7] have used heuristic approaches on spreadsheet templates to get near optimal solutions for the problem.

Evolutionary strategies and, in particular, genetic algorithms have been receiving considerable attention in many areas of the water resources industry. These methods have been successfully used for the optimal design of pipe networks with a fixed layout [8-12], the layout optimization of pipe and gas networks [13-16], management of groundwater systems [17-19], calibration of water resources models [20] and reservoir operation problems [21-24]. Genetic algorithms have proved to be very robust as these algorithms do not require the objective function continuity. They can be used for highly nonlinear convex and non-convex

1. *Department of Civil Engineering, Iran University of Science and Technology, Tehran, I.R. Iran.*

problems with or without dynamic characteristics. These interesting features of GA explain the wide range of successful applications of the method in different areas of water resources engineering.

In this paper, the application of a genetic algorithm to the optimal design of storm water networks is addressed. The performance of the method, using different selection methods, is studied. The efficiency of the method for storm water design is shown by applying the method to two benchmark examples in the literature and presenting the results. The method is shown to produce the best ever achieved solution to the problems considered.

PROBLEM FORMULATION

The problem of storm water network design, in its general form, may be formulated as:

$$\min Z = \sum_{i=1}^{n} f_i \quad d_i, \overline{Z}_i, C_i\big) , \tag{1}$$

subject to:

$$g_1 \equiv q_i \geq Q_i^*, \qquad \forall i, \tag{2}$$

$$g_2 \equiv V_i \leq V_{\max}, \qquad \forall i, \tag{3}$$

$$g_3 \equiv V_i \geq V_{\min}, \qquad \forall i, \tag{4}$$

$$g_4 \equiv \left(\frac{y}{d}\right)_i \leq \beta, \qquad \forall i, \tag{5}$$

$$g_5 \equiv S_i \geq S_{\min}, \qquad \forall i, \tag{6}$$

$$g_6 \equiv E_i \leq E_{\max}, \qquad \forall i, \tag{7}$$

$$g_7 \equiv E_i \geq E_{\min}, \qquad \forall i. \tag{8}$$

Here:

d_i	pipe diameter in link i,
$\overline{Z}_i$	average excavation depth for link i,
C_i	unit cost of excavation for link i,
q_i	flow rate in link i,
Q_i^*	design discharge in link i,
V_i	velocity in link i,
y_i	flow depth in link i,
S_i	slope of link i,
E_i	average pipe cover,
$V_{\min}$, $V_{\max}$	minimum and maximum velocity, respectively,
β	maximum allowable ratio of water to upon pipe diameter,
$E_{\min}$, $E_{\max}$	minimum and maximum average pipe cover, respectively,
$S_{\min}$	minimum permitted slope (more than zero in general),
n	total number of links in the network.

Genetic algorithms are basically designed for unconstrained optimization problems. Application of GA to constrained optimization problems, such as storm water networks, requires a transform of the underlying constrained problem to an unconstrained optimization problem. Penalty methods are usually used for this purpose, in which the constraints are included in the objective function via a penalty cost term, resulting in the following penalized form of the objective function:

$$\min Z_p = \sum_{i=1}^{n} f_i \quad d_i, \overline{Z}_i, C_i\big) + \alpha f(\mathbf{G}), \tag{9}$$

in which f is some function of the constraint violation matrix $\mathbf{G}$, with a typical component, g_{ij}, representing the jth constraint violation at pipe i and α representing the penalty parameter. Different forms of function f have been used by different researchers. One of the most used forms of function f is the maximum function, which uses the maximum constraint violation in Equation 9 [11,25-27]. In this method, GA could not distinguish between two different designs with the same maximum constraint violation but a different number of constraint violations. Here, a different form of the function is used. For this, first consider the normalized form of Constraints 2 to 8 as:

$$g_1 \equiv 1 \quad \frac{q_i}{Q_i^*} \leq 0, \qquad \forall i, \tag{10}$$

$$g_2 \equiv \frac{V_i}{V_{\max}} \quad 1 \leq 0, \qquad \forall i, \tag{11}$$

$$g_3 \equiv 1 \quad \frac{V_i}{V_{\min}} \leq 0, \qquad \forall i, \tag{12}$$

$$g_4 \equiv \frac{(\frac{y}{d})_i}{\beta} \quad 1 \leq 0, \qquad \forall i, \tag{13}$$

$$g_5 \equiv 1 \quad \frac{S_i}{S_{\min}} \leq 0, \qquad \forall i, \tag{14}$$

$$g_6 \equiv \frac{E_i}{E_{\max}} \quad 1 \leq 0, \qquad \forall i, \tag{15}$$

$$g_7 \equiv 1 \quad \frac{E_i}{E_{\min}} \leq 0, \qquad \forall i. \tag{16}$$

The penalized form of the objective function is now defined as:

$$\min Z_p = \sum_{i=1}^{n} f_i \quad d_i, \overline{Z}_i, C_i\big) + \sum_{j=1}^{7} \alpha_j \sum_{i=1}^{n} (g_{ij})^2, \tag{17}$$

where g_{ij} is the value of the jth constraint violation committed by the corresponding parameter of the ith pipe. Here, all the constraint violations are used for the penalty cost calculation. This method ensures that non-proper networks would have more penalty costs and, therefore, leads to a better distribution of the fitness function in the search space compared to the conventional method of helping GA to locate useful genes. The use of different penalty parameters for each of the constraints offers greater flexibility to the GA search engine to locate optimal or near optimal solutions, as will be discussed later.

GA FORMULATION

The following steps are taken in the GA search for optimal design of the storm water networks:

1. Encoding the design variables. The genetic algorithm requires that any trial solution of the design problem be represented by a coded string of finite length, similar to the structure of a chromosome of a genetic code. This is usually achieved by defining a selected mapping between the possible values of the design variables and a set of coded sub-strings with a required number of binary bits. For example, a four-bit sub-string can be coded to represent any of the 16 possible values of the design variables. Since nodal cover depth is used as a problem decision variable, a six-bit sub-string is used to represent the 64 possible values obtained by discretization of the range defined by the maximum and minimum allowable nodal cover depth;
2. Generation of an initial population. The GA randomly generates an initial population, of size N, of coded strings representing some trial solutions to the storm network design problem;
3. Computation of network cost. Each of the N members of the population is considered in turn and decoded to the corresponding nodal values of the cover depth. The largest possible diameter is then assumed for each pipe of the network, using the resulting pipe slopes, such that the constraint 13 is automatically satisfied. The cost of each trial solution of the current population is then calculated as the sum of the pipes and excavation costs;
4. Hydraulic analysis of the network. A steady-state analysis is carried out for each network of the current population to find the flow depth and velocity constraint violations. A home-made steady state simulation code is used to analyze the networks;
5. Computation of the total penalized cost. The penalty cost of the networks in the population is computed if the trial design does not satisfy all the constraints of the problem. The total penalized cost is considered as the sum of the network and penalty cost, as defined in Equation 17;
6. Computation of fitness. The fitness of a trial design is taken as some function of the total network cost. Investigators use different forms of the fitness functions [25,28]. Here, the deficit of the total cost from a big number (sum of the maximum and minimum total costs of the networks in the current generation) is used as the fitness of each network;
7. Generation of a new population. The GA generates the members of the new generation by a selection scheme. Different selection schemes are suggested in the literature. Here, four different selection schemes are considered, as follows:
    (a) Conventional Roulette Wheel Scheme (CRWS): In this scheme, the probability of a string i, p_i, to be selected for the next generation, is given by:
    $$p_i = \frac{f_i}{\sum_{i=1}^{N} f_i}. \tag{18}$$
    This scheme, however, is believed to be the source of the so-called pre-mature convergence, especially in small population genetic searches. Different remedies, in the form of scaling or alternative selection operators, are proposed to prevent the dominance of the extraordinary fit strings in the early stages of the search [29];
    (b) Roulette Wheel Scheme (RWS) with a Power Law Scaling: In this scheme, a scaling of the form $f_i' = f_i^\alpha$ is used, where the value of the exponent is designed so that $f'_{\text{max}} = 5f'_{\text{avg.}}$;
    (c) Roulette wheel scheme with a linear scaling: In this scheme, a linear scaling of the form $f_i' = af_i + b$ is used, where the value of the parameters are designed so that the raw and scaled average fitness have the same probability of selection and $f'_{\text{max}} = 5f'_{\text{avg}}$;
    (d) Roulette wheel scheme with ranking: In this scheme, the population is first ordered according to the computed fitness values and parents are selected with a probability based on their rank in the population [30].
8. The crossover operation. Two off-springs are formed via the partial exchange of bits between two selected parents, using a crossover operator. Crossover occurs with some specified probability of crossover, p_c, for each pair of parents selected in the previous step. Here, a one-point cross-over is used in which a point is randomly selected on the strings and, then, the bits before the selected point are exchanged to form two off-springs;
9. Mutation. A bit-wise mutation with some specified probability of mutation, p_m, is carried out for each of the strings which have undergone crossover. The bit-wise mutation changes the value of the selected bit to the opposite value (i.e., 0 to 1 or 1 to 0). A one-bit mutation is used in this work;

Table 1. Data of the first benchmark example.

Link	Ground Elevation (m)		Length (m)	Design Discharge (Cm)
	Upstream	Downstream		
1122	152.4	150.876	106.68	0.1132
2233	150.876	148.4876	121.92	0.1982
3342	148.4876	146.304	106.68	0.2548
1232	149.352	147.828	121.92	0.1132
3242	147.828	146.304	131.0761	0.2265
4252	146.304	143.256	167.6796	0.6229
2334	149.352	147.828	147.6375	0.2265
3443	147.828	144.78	137.16	0.3398
4352	144.78	143.256	106.68	0.453
5261	143.256	141.732	152.4	1.2459
3141	147.828	144.78	152.4	0.2548
4151	144.78	143.256	106.68	0.453
5161	143.256	141.732	106.68	0.5663
6171	141.732	138.648	172.212	2.0104
4453	142.6464	141.4272	121.92	0.1132
5362	141.4272	140.208	91.44	0.1699
6271	140.208	138.648	105.2291	0.2548
7181	138.648	137.4648	121.92	2.4635
8191	137.4648	136.5504	152.4	2.5201
9110	136.5504	135.636	186.5376	2.6617

10. Production of successive generations. The three operators described above produce a new generation of network trial designs. This procedure is repeated to create successive generations. Typically, a GA will evaluate between 100 and 1000 generations, depending on the problem size. Here, the GA run is allowed for 1000 generations to make sure of the convergence of the different selection schemes used.

MODEL APPLICATION

The performance of the proposed GAs is investigated in this section by applying the model to solve two benchmark problems in the literature. The first example to be considered is a problem originally designed by Mays and Wenzel [31] and solved by various investigators. The test problem includes 20 links and 21 nodes, as shown in Figure 1. Table 1 presents the characteristic data of the test problem. This problem is constrained to have a maximum velocity of 12 fps (3.6 m/s), a minimum velocity of 2 fps (0.6 m/s) and a minimum cover of 8 ft (2.4 m). Mays and Wenzel [31] first used this problem to test the Discrete Differential Dynamic Programming (DDDP) model they proposed. The DDDP is an iterative technique in which the recursive equation of DP is used to search for an improved trajectory among the discrete states in the

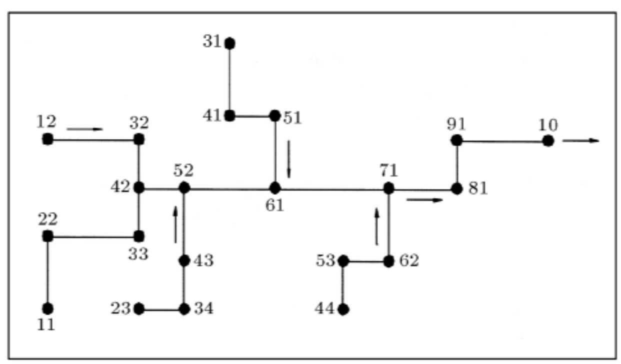

Figure 1. Network layout for the first example.

neighborhood of a trial solution [32]. The problem was later solved by Robinson and Labadie [1] with a different version of the dynamic programming model. Miles and Heaney [6] and Afshar and Zamani [7] approached this problem in a spread sheet template. Figure 2 shows the convergence characteristics of the GA methods during the evolution process, while Table 2 presents and compares the results obtained from the proposed GA methods from the other results in the literature. These results are obtained with a population size of 200, a one-point crossover, $p_c = 1$, and a one-bit mutation per chromosome, $p_m = 0.5$. The best result (202496 units) is obtained with the conventional Roulette Wheel scheme within 145200 evaluations. The good performance of this selection scheme, which is known for premature convergence, can be attributed to the relatively long sub-strings (64 bit) used to represent the allowable variation of the decision variables, resulting in a very large search space. The RWS with linear scaling showed much faster characteristics, yielding the second best result (205191 units). This result is obtained at the expense of 50000 network evaluations, much less than the number of analyses required by the CRWS. The two other selection schemes showed the same convergence characteristics with similar poorer results. The RWS with ranking converged to a solution with 217729 units of cost within 66000 function evaluations, while the RWS with power law scaling resulted in a solution with 213000 units of cost in about 65000 network simulations. Despite different results obtained by the proposed GA method, the resulting solutions are all cheaper than the best ever achieved solution in the literature. This example shows the efficiency and effectiveness of the genetic algorithm in solving storm water network design problems compared to the existing methods. Details of the optimal solution obtained by the proposed methods are shown in Tables 3 to 6. The best ever result reported in the literature is obtained by Afshar and Zamani [7], using a heuristic approach in a spreadsheet template, which is also shown in Table 7 for comparison.

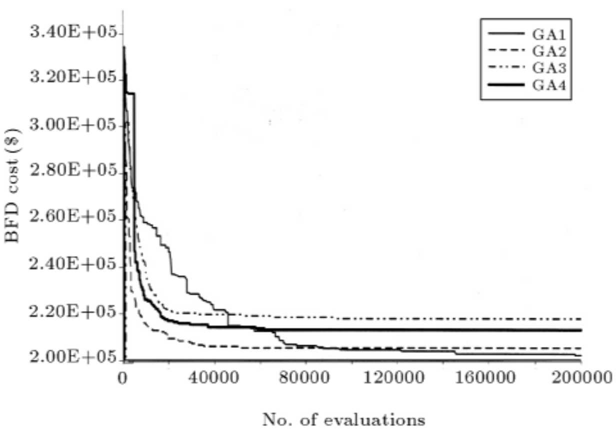

Figure 2. Best feasible cost solution of the generations during the evolution process.

Table 2. Optimal network cost obtained by different models for the first example.

Model	Cost (units)
Mays and Wenzel [31]	265,775
Robinson and Labadie [1]	275,218
Miles and Heaney (spreadsheet) [6]	245,874
Afshar and Zamani [7]	221,652
Present model (GA1)	202,496
Present model (GA2)	205,191
Present model (GA3)	217,729
Present model (GA4)	213,000

The second example is a network with 9 links and 10 nodes, shown in Figure 3. This network was used by Afshar and Zamani [7] to test their model against the SEWER software developed by the World Bank [33]. Physical and hydrological data of the network are given in Afshar and Zamani [7]. Table 8 shows the cost of the optimal solution obtained with different methods, including the proposed GA methods, while the details of the optimal solution obtained by the proposed methods are shown in Tables 9 to 12. Two of the proposed methods resulted in cheaper solutions than previously obtained, while the other two converged to networks with marginally higher costs. The best result is again obtained by the Conventional Roulette Wheel Scheme. The reason GA could not improve the solution as much as the first example is mostly due to the fact that the second problem is a very easy problem. This is clearly seen by the marginal improvement achieved by the previous model, with respect to the result obtained by SEWER, which is a very basic design code for sewer networks.

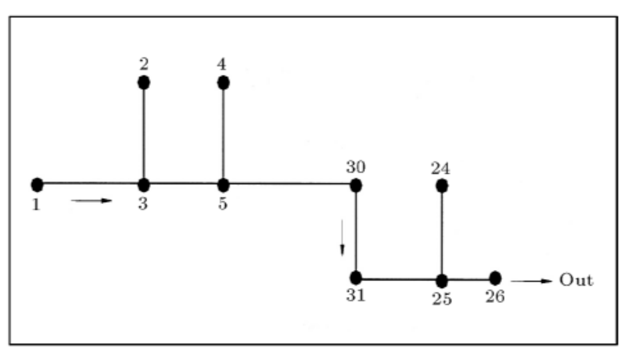

Figure 3. Network layout for the second example.

Table 3. Results obtained from GA1 for the first example.

Link	Crown Elevation (m)		Diameter (mm)	Velocity (m/s)
	Upstream	Downstream		
11-22	150	148.476	304.8	1.877
22-33	148.476	146.0876	381	2.4788
33-42	146.0876	143.9040	381	2.6151
12-32	146.952	144.9383	304.8	2.0008
32-42	144.9383	143.9040	457.2	1.8093
42-52	143.9040	140.4933	533.4	3.2659
23-34	146.952	144.5574	381	2.3277
34-43	144.5574	142.38	457.2	2.5864
43-52	142.38	140.4933	533.4	2.939
52-61	140.4933	138.2742	762	3.4784
31-41	145.428	142.38	381	2.5858
41-51	142.38	140.8560	533.4	2.6929
51-61	140.8560	138.2742	533.4	3.4811
61-71	138.2742	136.2480	914.4	3.5651
44-53	140.2464	138.5467	304.8	1.8560
53-62	138.5467	137.7476	381	1.7094
62-71	137.7476	136.2480	457.2	2.3525
71-81	136.2480	135.0648	1066.8	3.5509
81-91	135.0648	133.8504	1066.8	3.2538
91-10	133.8504	132.2087	1066.8	3.4195

Table 4. Results obtained from GA2 for the first example.

Link	Crown Elevation (m)		Diameter (mm)	Velocity (m/s)
	Upstream	Downstream		
11-22	150	148.476	304.8	1.877
22-33	148.476	146.0876	381	2.4788
33-42	146.0876	143.9040	381	2.6151
12-32	146.952	145.3736	304.8	1.7916
32-42	145.3736	143.9040	457.2	2.0876
42-52	143.9040	140.4480	533.4	3.2865
23-34	146.952	144.6662	381	2.2752
34-43	144.6662	142.38	457.2	2.6419
43-52	142.38	140.4480	533.4	2.9671
52-61	140.4480	138.0627	762	3.5874
31-41	145.428	142.38	381	2.5858
41-51	142.38	140.8560	533.4	2.6929
51-61	140.8560	138.0627	533.4	3.5948
61-71	138.0627	136.0418	914.4	3.5605
44-53	140.2464	138.6428	304.8	1.8055
53-62	138.6428	137.8080	381	1.7464
62-71	137.8080	136.0418	457.2	2.5084
71-81	136.0418	135.0648	1066.8	3.2599
81-91	135.0648	133.7503	1066.8	3.3789
91-10	133.7503	132.1060	1066.8	3.4223

Table 5. Results obtained from GA3 for the first example.

Link	Crown Elevation (m)		Diameter (mm)	Velocity (m/s)
	Upstream	Downstream		
11-22	150	148.476	304.8	1.877
22-33	148.476	146.0876	381	2.4788
33-42	146.0876	143.5942	381	2.7792
12-32	146.952	145.3736	304.8	1.7916
32-42	145.3736	143.5942	457.2	2.2500
42-52	143.5942	139.4053	533.4	3.5822
23-34	146.952	144.5574	381	2.3277
34-43	144.5574	142.38	457.2	2.5864
43-52	142.38	139.4053	457.2	3.4301
52-61	139.4053	137.6396	762	3.1316
31-41	145.428	142.38	381	2.5858
41-51	142.38	140.3573	533.4	3.0219
51-61	140.3573	137.6396	533.4	3.5550
61-71	137.6396	136.2480	1066.8	3.1798
44-53	140.2464	138.6428	304.8	1.8055
53-62	138.6428	137.8080	381	1.7464
62-71	137.8080	136.2480	457.2	2.3895
71-81	136.2480	135.0648	1066.8	3.5509
81-91	135.0648	133.8504	1066.8	3.2538
91-10	133.8504	132.2087	1066.8	3.4195

Table 6. Results obtained from GA4 for the first example.

Link	Crown Elevation (m)		Diameter (mm)	Velocity (m/s)
	Upstream	Downstream		
11-22	150	148.476	304.8	1.877
22-33	148.476	146.0876	381	2.4788
33-42	146.0876	143.9040	381	2.6151
12-32	146.952	145.3736	304.8	1.7916
32-42	145.3736	143.9040	457.2	2.0876
42-52	143.9040	139.9040	533.4	3.5114
23-34	146.952	144.5574	381	2.3277
34-43	144.5574	142.38	457.2	2.5864
43-52	142.38	139.9040	457.2	3.1475
52-61	139.9040	137.8511	762	3.3614
31-41	145.428	142.38	381	2.5858
41-51	142.38	140.4933	533.4	3.9390
51-61	140.4933	137.8511	533.4	3.5143
61-71	137.8511	135.8356	914.4	3.5559
44-53	140.2464	138.6428	304.8	1.8055
53-62	138.6428	137.8080	381	1.7464
62-71	137.8080	135.8356	457.2	2.6178
71-81	135.8356	134.8702	1066.8	3.2415
81-91	134.8702	134.1504	1219.2	3.7187
91-10	134.1504	132.4142	1066.8	3.5138

Table 7. Results reported by Afshar and Zamani [7].

Link	Crown Elevation (m)		Diameter (mm)	Velocity (m/s)
	Upstream	Downstream		
11-22	150	148.36	304.8	1.66
22-33	148.38	146	381	2.25
33-42	145.84	143.76	381	2.25
12-32	146.91	145.35	304.8	1.57
32-42	145.27	143.9	457.2	1.86
42-52	143.60	140.35	533.4	2.8
23-34	146.95	145.4	457.2	1.86
34-43	145.29	142.38	457.2	2.64
43-52	142.16	140.85	533.4	2.23
52-61	140.10	138.8	914.4	2.66
31-41	145.4	142.38	381	2.56
41-51	142.22	140.8	533.4	2.32
51-61	140.63	138.9	533.4	2.26
61-71	138.58	136.03	914.4	3.49
44-53	140.24	138.7	304.8	1.56
53-62	138.62	137.75	381	1.57
62-71	137.67	136.28	457.2	2.09
71-81	135.65	135.06	1219.2	2.42
81-91	134.87	134.15	1219.2	2.4
91-10	133.97	131.8	1066.8	3.43

Table 8. Cost of the optimal network obtained for the second example.

Model	Cost
SEWER (World Bank)	199,480
Afshar and Zamani [7]	199,320
Present model (GA1)	198,873
Present model (GA2)	199,514
Present model (GA3)	199,647
Present model (GA4)	199,237

Table 9. Results obtained from GA1 for the second example.

Link	Crown Elevation (m)		Diameter (mm)	Velocity (m/s)
	Upstream	Downstream		
1-3	1394.6	1386.7667	150	2.0573
2-3	1393.9	1387.1000	250	2.0532
3-5	1387.1000	1380.0667	300	2.4834
4-5	1385.5	1380.0667	300	2.3450
5-30	1380.0667	1378.1190	450	2.489
30-31	1378.1190	1377.5000	450	2.2016
31-25	1377.5000	1374.4762	450	2.4347
24-25	1376. 6143	1374.4762	150	2.436
25-26	1374.4762	1371.0	500	2.4980

Table 10. Results obtained from GA2 for the second example.

Link	Crown Elevation (m)		Diameter (mm)	Velocity (m/s)
	Upstream	Downstream		
1-3	1394.6	1386.3381	150	2.1321
2-3	1393.9	1386.3381	250	2.1406
3-5	1386.3381	1379.4476	300	2.4627
4-5	1385.5	1379.4476	300	2.4497
5-30	1379.4476	1377.5476	450	2.4639
30-31	1377.5476	1376.7381	450	2.4835
31-25	1376.7381	1374.3810	450	2.1719
24-25	1376. 5190	1374.3810	150	2.4936
25-26	1374.3810	1371.0	500	2.4696

Table 11. Results obtained from GA3 for the second example.

Link	Crown Elevation (m)		Diameter (mm)	Velocity (m/s)
	Upstream	Downstream		
1-3	1394.6	1386.3381	150	2.1321
2-3	1393.9	1386.3381	250	2.1406
3-5	1386.3381	1379. 2571	300	2.4902
4-5	1385.5	1379. 2571	300	2.4802
5-30	1379. 2571	1377. 3571	450	2.4639
30-31	1377. 3571	1376.7381	450	2.2016
31-25	1376.7381	1374.3810	450	2.1719
24-25	1376. 1381	1374.3810	150	2.2778
25-26	1374.3810	1371.0	500	2.4696

Table 12. Results obtained from GA4 for the second example.

Link	Crown Elevation (m)		Diameter (mm)	Velocity (m/s)
	Upstream	Downstream		
1-3	1394.6	1386.7190	150	2.0953
2-3	1393.9	1386.7190	250	2.0977
3-5	1386.7190	1379.6381	300	2.4902
4-5	1385.5	1379.6381	300	2.4184
5-30	1379.6381	1377.7381	450	2.4639
30-31	1377.7381	1377.1190	450	2.2016
31-25	1377.1190	1374.4762	450	2.2940
24-25	1376.6143	1374.4762	150	2.4936
25-26	1374.4762	1371.0	500	2.4980

CONCLUDING REMARKS

A genetic algorithm is proposed for the optimal design of storm water networks. The performance of four different selection schemes is tested by solving two benchmark problems in the literature. The Conventional Roulette Wheel Selection Scheme proved to be the most efficient method regarding the optimality of the solution. The Roulette Wheel Selection Scheme with linear scaling, however, showed superior convergence characteristics, yielding a near optimal solution compared to the conventional scheme. All GA methods resulted in cheaper solutions, compared to the previous results obtained for the larger first example. The GA method failed to considerably improve previous results for the smaller network, mostly due to the simplicity of the considered network. This shows that genetic algorithms might be most efficient for solving large scale real-world problems where other methods often fail.

REFERENCES

1. Robinson, D.K. and Labadie, J.W. "Optimal design of urban storm water drainage system", *Int. Symposium on Urban Hydrology, Hydraulics, and Sediment Control*, University of Kentucky, Lexington, KY, USA, pp 145-156 (1981).
2. Yen, B.C., Cheng, S.T., Jun, B.H., Voohees, M.L. and Wenzel, H.G. "Illinois least cost sewer system design model, user's guide", Dept. of Civil Engineering, University of Texas at Austin, USA (1984).
3. Kulkarin, V.S. and Khanna, P. "Pumped wastewater collection systems optimization", *J. of Environmental Engineering, ASCE*, **111**(5), pp 589-601 (1985).
4. Li, G., and Matthew, R.G.S. "New approach for optimization of urban drainage systems", *J. of Environmental Engineering, ASCE*, **116**(5), pp 927-944 (1990).
5. Elimam, A.A., Charalambous, C. and Ghobrial, F.H. "Optimum design of large sewer networks", *J. of Environmental Engineering, ASCE*, **115**(6), pp 1171-1189 (1989).
6. Miles, S.W. and Heaney, J.P. "Better than optimal method for designing drainage systems", *J. of Wat. Resour. Plng. and Mgmt., ASCE*, **114**(5), pp 477-499 (1988).
7. Afshar, A. and Zamani, H. "An improved storm water network design model in spreadsheet template", *Int. J. of Engrg. and Science*, Iran University of Science and Technology, **13**(4), pp 135-148 (2002).
8. Goldberg, D.E. and Kuo, C.H. "Genetic algorithms in pipeline optimization", *J. of Computing in Civil Engineering, ASCE*, **1**(2), pp 128-141 (1987).
9. Murphy, L.J., Simpson, A.R. and Dandy, G.C. "Design of a network using genetic algorithms", *Water*, **20**, pp 40-42 (1993).
10. Simpson, A.R., Dandy, G.C. and Murphy, L.J. "Genetic algorithms compared to other techniques for pipe optimization", *J. of Wat. Resour. Plng. and Mgmt., ASCE*, **120**(4), pp 423- 443 (1994).
11. Savic, D.A. and Walters, G.A. "Genetic algorithms for least-cost design of water distribution networks", *J. of Wat. Resour. Plng and Mgmt., ASCE*, **123**(2), pp 67-77 (1997).
12. Wu, Z.Y. and Simpson, A.R. "Competent genetic evolutionary optimization of water distribution system", *J. of Comput. Civil Eng.*, **15**(2), pp 89-101 (2001).
13. Davidson, J.W. and Goulter, I.C. "Evolution program for the design of rectilinear branched distribution systems", *J. of Computing in Civil Engineering, ASCE*, **9**(2), pp 112-121 (1995).
14. Walters, G.A. and Lohbeck, T.K., "Optimal layout of tree networks using genetic algorithms", *Engineering Optimization*, **22**, pp 27-48 (1993).
15. Walters, G.A. and Smith, D.K. "Evolutionary design algorithm for optimal layout of tree networks", *Engineering Optimization*, **24**, pp 261-268 (1995).
16. Davidson, J.W. "Evolution program for layout geometry of rectilinear looped networks", *Journal of Computing in Civil Engineering, ASCE*, **13**(4), pp 246-253 (1999).
17. McKinney, D.C. and Lin, M.D. "Genetic algorithm solution of groundwater management models", *Water Resour. Res.*, **30**(6), pp 1897-1906 (1994).
18. Ritzel, B.J., Ehearrt, J.W. and Ranjithan, S. "Using genetic algorithms to solve a multiple objective groundwater pollution problem", *Water Resour. Res.*, **30**(5), pp 1589-1603 (1994).
19. Cieniawski, S.E., Eheart, J.W. and Ranjithan, S. "Using genetic algorithms to solve a multi-objective groundwater monitoring problem", *Water Resour. Res.*, **31**(2), pp 399-409 (1995).
20. Wan, B. and James, W. "SWMM calibration using genetic algorithms", Chapter 7 in *Best Modelling Practice for Urban Water Systems*, Monograph 10 published by CHI, Guelph, Ontario, Canada, ISBN 0-9683681-6-6 CHI catalog Number. R208 (2002).
21. Esat, V. and Hall, M.J. "Water resources system optimization using genetic algorithms." *Hydroinformatics 94, Proc., 1st. Int. Conf. on Hydroinformatics*, Balkema, Rotterdam, The Netherlands, pp 225-231 (1994).
22. Fahmy, H.S., King, J.P., Wentzel, M.W. and Seton, J.A. "Economic optimization of river management using genetic algorithms", *Int. Summer Meeting, Am. Soc. Agric. Engrs.* (943034), St. Joseph, Mich, USA (1994).
23. Oliveira, R. and Loucks, D.P. "Operating rules for multi-reservoir systems", *Water Resour. Res.*, **33**(4), pp 839-852 (1997).
24. Wardlaw, R. and Sharif, M. "Evaluation of genetic algorithms for optimal reservoir system operation", *J. of Wat. Resour. Plng. and Mgmt., ASCE*, **125**(1), pp 25-33 (1999).
25. Dandy, G.C., Simpson, A.R. and Murphy, L.J. "An improved genetic algorithm for pipe network optimization", *Wat. Resour. Res.*, **32**(2), pp 449-458 (1996).
26. Abebe, A.J. and Solomatine, D.P. "Application of global optimization to the design of pipe networks", *3rd Int. Conf. on Hydroinformatics*, Copenhagen, pp 989-996, Balkema, Netherlands (1999).
27. Boulos, P.F., Wu, Z.Y., Orr, C.H. and Ro, J.J. "Least-cost design and rehabilitation of water distribution systems using genetic algorithms", *Proceedings of the AWWA IMTech Conference*, April 16-19, Seattle, WA, USA (2000).

28. Gen, M. and Cheng, R., *Genetic Algorithms and Engineering Design*, John Wiley & Sons, NY, USA (1997).

29. Goldberg, D.E., *Genetic Algorithms in Search, Optimization & Machine Learning*, Addison-Wesley publishing Co, Reading, UK (1989).

30. Grefenstette, J.J. and Backer, J.E. "How genetic algorithms work: A critical look at implicit parallelism", *Proc., 3rd Int. Conf. of Genetic Algorithms*, J.D. Schaffer, Ed., Morgan Kaufmann Publishers, San Mateo, Calif., USA pp 20-27 (1989).

31. Mays, L.W. and Wenzel, H.G. "Optimal design of multi-level branching sewer systems", *Water Resour. Res.*, **12**(5), pp 913-917 (1976).

32. Heidari, M., Chow, V.T., Kokotovic, P.V., Meredith, D.D. "Discrete differential dynamic programming approach to water resources systems optimization", *Water Resou. Res.*, **7**(2), pp 273-282 (1971).

33. World Bank, SEWER design package, New York, USA (1991).