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Abstract This work aims at introducing an optimization model to design sewer networks. The approach specially focuses on handling the nonlinear and discrete constraints of the problem. For this purpose, an adaptive genetic algorithm is developed so that every chromosome, consisting of sewer diameters and slopes and pump indicators, is a feasible design. The binary chromosomes are freely generated and then decoded to feasible design alternatives following a sequential design-analysis algorithm. The adaptive decoding strategy is set up based on the open channel hydraulics and sewer design criteria. Through the proposed method, all the sewer system's constraints are systematically satisfied. Consequently, there is neither need to discard or repair infeasible chromosomes nor to apply penalty factors to the cost function. A benchmark sewer network from the literature is considered to be designed using the proposed approach. The obtained results are then discussed and compared with the previous works. It is found that the adaptive constraint handling method computationally makes the optimization more efficient in terms of speed and reliability.

Keywords Sewer networks · Optimization · Adaptive genetic algorithm · Constraint handling

1 Introduction

Sewer networks are essential urban infrastructures which directly influence the public health. Constructing a new sewer system, particularly in populous cities, is a very expensive and difficult task. This issue has motivated the engineers and researchers to develop and exploit optimization methods for obtaining cost-effective designs. The sewer networks optimization problem consists of many hydraulic and technical constraints which are mostly sequential, nonlinear and discrete. Satisfying such constraints to give a feasible design is often burdensome and time-consuming even for small systems even by experienced engineers. In this regard, mathematical programming

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methods and optimization tools are very helpful while handling the problem constraints plays a major role in efficiency and reliability of the applied methods. In general, taking a lot of time numerical optimization methods offer numerous solutions to the problem at hand. The ability to find the global optimum solution as well as the capability of fast converging are main aspects of any optimization method. These issues are dependent on the optimization algorithm on one side and on the problem definition and its mathematical specifications on the other side. Sewer networks design is mathematically a high-level sequential decision making problem which cannot be solved by classical gradient-based optimization methods. For such problems, Discrete Differential Dynamic Programming (DDDP) is a powerful approach which has been successfully applied to various fields of water resources (Heidari et al. 1971) as well as to optimization of sewer systems (Mays and Yen 1975; Mays et al. 1976; Mays et al. 1976; Li and Matthew 1990). DDDP breaks a continuous decision space into a limited number of solutions among which the optimum design is then sought. Although this trick is very useful for discreet nonlinear problems and makes them more tractable to be solved but the chance of finding the global optima may reduce. In addition, the DDDP's stages must be manually divided and defined by the user. This can be sometimes hard to apply and time-consuming (Pan and Kao 2009) especially for large-scale problems.

In recent years, metaheuristic methods mostly inspired by nature have been highly developed and widely applied to complex engineering problems such as water networks (Reca et al. 2008). Ant Colony (Afshar 2010), Particle Swarm Optimization (Ostadrahimi et al. 2012) and Genetic Algorithms (GA) are some famous metaheuristics applied to water and sewer engineering problems. GA is developed based on the principles of the natural-random evolution of a population. This method has been already applied to optimization of sewer networks (Liang et al. 2004; Afshar et al. 2006) and resulted in good performances with no need to restrict the decision space as is required in DDDP. Genetic algorithms are inherently unconstrained techniques. GAs slowly progress in a random-based framework and this is why they are not computationally efficient compared to mathematical methods. As the number of variables and constraints increase the weak point of GAs in speed becomes more serious. As a remedy for this problem, hybrid optimization models can be very useful. For instance, Cisty (2010) and Haghighi et al. (2011) respectively hybridized the GA with Linear Programming (LP) and Integer Linear Programming (ILP) for optimization of water supply networks. In this context, Pan and Kao (2009) developed an interesting hybrid method for sewer networks design. In that work, the mathematical method of quadratic programming (QP) was considered as the inner solver and coupled with a GA as the outer solver. Most of sewer constraints and variables were skillfully formulated in QP, and this significantly improved the method's efficiency. Other constraints like the one related to the sewer diameters were handled in the GA. In spite the remarkable features of that approach, implementing the QP-GA model is much more complex than the previous methods like DDDP or GA alone.

It is believed here that handling the constraints has the most effective role in optimizing sewer networks and is therefore focused in this work. For this purpose, an adaptive binary genetic algorithm is so developed that all the sewer design constraints are systematically satisfied thereby the construction cost function is freely minimized. In what follows, the method is described in details and a benchmark case study from the literature is finally taken into account to be optimized using the proposed scheme.

2 Sewer Hydraulics

Steady-state flow in sewers is described by the continuity principle ($Q = VA$) and Manning's equation which in metric system is:

$$V = \frac{1}{n} R^{2/3} S^{1/2} \tag{1}$$

where A = flow cross-sectional area, Q = sewage flow rate, n = Manning's coefficient, R = hydraulic radius and S = sewer slope. Common geometrical specifications for circular sections are also obtained from the following equations:

$$(h/D) = \frac{1}{2} \times \left(1 - \cos\frac{\theta}{2}\right) \tag{2}$$

$$\frac{A}{A_0} = \left(\frac{\theta - \sin\theta}{2\pi}\right) \tag{3}$$

$$R = \frac{D}{4} \times \left(\frac{\theta - \sin\theta}{\theta}\right) \tag{4}$$

where D = pipe diameter, A_0 = pipe cross-sectional area, (h/D) = proportional water depth and θ = the central angle from the center of the section to the water surface (in radian).

3 Design Constraints

For a given layout, a feasible sewer design is defined as a set of pipe diameters [D], slopes [S] and pump location indicators [P] which satisfies all the constraints. Referring to Pan and Kao (2009), typical constraints of sewer networks design are:

1- Keeping flow velocity between minimum and maximum bounds respectively for self-cleaning capability and preventing from scouring,
2- For each manhole, placing upstream pipes at higher elevations than the downstream one,
3- Maintaining the proportional water depth under the specified maximum value,
4- Choosing sewer diameters from the commercial list,
5- Maintaining the minimum buried depth to prevent damages from the traffic loads and other surface activates and,
6- For each manhole, assigning the outlet pipe's diameter equal to or greater than the upstream inlet pipes'.

For every feasible design, the construction cost is estimated from the following equation. It is also taken into account as the objective function of optimization in this work:

$$C(D, S, P) = \sum_{i=1}^{NP} (CP_i + P_i \times CL_i) + \sum_{i=1}^{NP+1} CM_i \tag{5}$$

in which C = cost function; CP and CM = respectively, construction cost of sewers and manholes those are estimated as a function of pipe diameter and buried depth; CL =

construction cost of pump stations, generally estimated as a function of sewer flow rate, NP = Number of pipes, and P=1 if there is a pump at the upstream end of the pipe and zero otherwise.

4 Sewer Networks Optimization

For optimization of sewer networks, a simple binary genetic algorithm is developed which is equipped with an adaptive procedure for systematically handling the constraints. As follows, the characteristics of the proposed model are described along with a brief review on the applied GA:

Chromosomes:

In the GA terminology a chromosome is a vector of variables to be optimized. In binary GA, real decision variables are encoded with binary 0-1 values (bits). Each chromosome represents a design alternative which can be potentially feasible or not. In the sewer design problem, there are $3NP$ variables including NP pipe diameters, NP slopes and NP pump location indicators. To get the least-cost design, these variables need to be calibrated by GA to minimize the cost function of Eq. 5. Considering N_b binary bits to represent each parameter in [D] and [S] and one bit for each parameter in [P], a design chromosome is consisting of $(2N_b+1)NP$ genes (0-1 values) as shown in Fig. 1.

Population:

GA starts to optimize the problem with an initial population of chromosomes which are randomly generated in the beginning. The chromosomes evolve through successive iterations namely generations in GA (Gen and Cheng 1997). Deciding about the population size, N_{pop}, is greatly dependent on the problem size and its mathematical specifications. However, some preliminary sensitivity analysis and the user experiences on GAs are quite substantial in this regard. Herein, the initial population is randomly generated as a binary matrix with N_{pop} rows and $(2N_b+1)NP$ columns.

5 Handling Constraints

When using standard GAs for optimization of sewer networks, initial population is randomly produced and then by random-based operators next generations are created. This mechanism often results in infeasible chromosomes which are not accepted for cost evaluation. For handling the aforementioned sewer constraints and avoiding infeasible solutions, several techniques have been so far proposed for metaheuristics. These techniques can be simply classified as the rejecting, repairing, penalizing and modifying strategies (Gen and Cheng 1997). Except the last one which is also referred to as adaptive strategy the others let

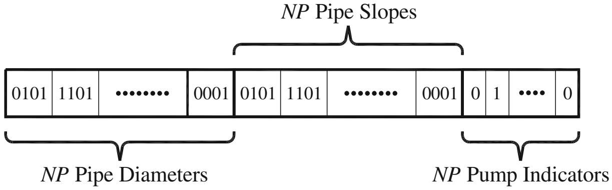

Fig. 1 Binary chromosome of a design alternative

infeasible solutions be created and then GA may discard or repair them (e.g., Pan and Kao 2009) or be forced to move away from them by posing penalty factors (e.g., Van Zyl et al. 2004; Kadu et al. 2008; Shamloo and Haghighi 2010). The modifying or adaptive strategy helps the designer develop an adaptive genetic algorithm in which the method operators are systematically adapted with respect to the problem constraints. The adaptive operators always keep the GA in feasible regions of the decision space and consequently improve the optimization performance in terms of speed and reliability.

Following the sewer design hydraulics and technical constraints, an adaptive scheme is coupled with a simple GA. In this approach, binary chromosomes are freely produced, mated and mutated. They are then manipulated by the especial operators in such a manner that all the constraints are met in two decoding stages as follows:

Stage 1: In the beginning of this stage, the binary initial population is available in which each row is a chromosome representing a design alternative. For each chromosome, sewer diameters [D] and slopes [S] previously encoded as N_b bits are now decoded to normal real values in interval [0, 1]. This is done using the following relationship (Haupt and Haupt 2004) for example for diameters:

$$d_j = \sum_{i=1}^{N_b} gene_i \times 2^{-i} + gene_{N_b} \times 2^{-N_b} \tag{6}$$

where $gene_i$ = i^{th} gene in the binary string representing D_j in the chromosome being decoded and d_j = normal diameter value of pipe j in the system. Similarly, Eq. 6 is applied to decoding pipe slopes. The vectors of normal pipe diameters [d] and normal pipe slopes [s] with NP members are eventually obtained. The last NP genes in the chromosome (Fig. 1.) do not need to be decoded since they directly indicate the vector of pump locations [P].

At the end of this stage, the binary chromosomes have been interpreted in normal design parameters which are not yet technically understandable. In addition, the problem constraints have still remained to be satisfied. These issues are addressed in the next stage of chromosomes decoding.

Stage 2: In this stage, the normal-value chromosomes are step by step decoded to the feasible designs:

Pipe diameters: From the previous stage, every pipe has a normal diameter d_i which is decoded to a design value D_i using the following equation:

$$D_i = D_{\min,i} + \left(D_{\max,i} - D_{\min,i}\right) \times d_i \tag{7}$$

in which $D_{\min,i}$ and $D_{\max,i}$ = respectively, the minimum and maximum permissible diameter size for pipe i. $D_{\max,i}$ is in fact the largest diameter size in the commercial list, the vector [DC]. However, $D_{\min,i}$ is determined subject to two basic constraints. Firstly, the pipe must be capable of conveying the design flow rate Q_i and consequently be true for the following constraint (Pan and Kao 2009):

$$\frac{Q_i}{V_{\max}} \le \left(\frac{A}{A_0}\right)_{(h/D)_{\max}} \times \left(\frac{D_i^2}{4} \times \pi\right) \tag{8}$$

where V_{max} = maximum permissible flow velocity and $(h/D)_{\max}$ = maximum permissible proportional water depth. Substituting $(h/D)_{\max}$ in Eq. 2, $\theta_{\max}$ is explicitly achieved from:

$$\theta_{\max} = 2\cos^{-1}\left(1 - 2 \times (h/D)_{\max}\right) \tag{9}$$

Substituting (9) in (3), the proportional area (A/A_0) is also calculated. Afterwards, a lower bound for D_i is obtained from (8). Secondly, sewer pipes in the network should follow a telescopic pattern in terms of size so that:

$$D_i \geq \max[DU] \tag{10}$$

where $[DU]$ is the vector of pipe diameters connected to the upstream end of pipe i. Between the criteria (8) and (10), each one results in a greater diameter is considered as $D_{\min,i}$ and substituted in (7). The design diameter D_i is now determined which of course needs to be rounded to the first larger size in the commercial list $[DC]$. The proposed algorithm is sequentially applied to all pipes in such a way that the upstream branches (chord links) in the network spanning tree are initially taken into account. The algorithm is then applied to the remained pipes whose $[DU]$ vectors have been already completed. This approach is step by step followed until the whole network is covered. Accordingly, the sewer design diameters $[D]$ are identified from the normal real values $[d]$ extracted from the initial binary chromosomes.

Pipe slopes: There is also a vector of normal-value pipe slopes $[s]$ to be decoded in this stage. In analogy with Eq. 7, the design pipe slopes are obtained from:

$$S_i = S_{\min,i} + \left(S_{\max,i} - S_{\min,i}\right) \times s_i \tag{11}$$

where S_i = pipe slope, $S_{\min,i}$ and $S_{\max,i}$ = respectively, the minimum and maximum permissible slopes for pipe i. For assigning $S_{\min,i}$, three constraints must be satisfied. Firstly, all pipe slopes must be greater than a least construction value denoted by S_c herein:

$$S_i \geq S_c \tag{12}$$

Secondly, knowing the pipe diameter and flow rate, the slope should satisfy the restriction of maximum proportional water depth. For pipe i, the maximum central angle $\theta_{\max}$ was already calculated from Eq. 9. S_i should be therefore:

$$S_i \geq (n_i Q_i)^2 \times \left(\left(AR^{2/3}\right)_{\theta_{\max}}\right)^{-2} \tag{13}$$

And thirdly, the flow velocity in the pipe must be kept higher than the minimum velocity V_{min} meaning that:

$$S_i \geq (n_i V_{\min})^2 \times \left(\left(R^{2/3}\right)_{\theta_{\min}}\right)^{-2} \tag{14}$$

in which $\theta_{\min}$ is implicitly obtained by substituting V_{min} in Manning's equation which is then numerically solved by means of Newton–Raphson method.

Eventually, from Eqs. 12 to 14 the largest slope is selected as the pipe minimum slope $S_{\min,i}$ which covers all the above constraints.

For $S_{\max,i}$, there is only one restriction which is related to keeping the pipe flow velocity less than V_{max}. This constraint is also formulated as follows:

$$S_i \le (n_i V_{\max})^2 \times \left(\left(R^{2/3} \right)_{\theta'_{\max}} \right)^{-2} \tag{15}$$

where $\theta'_{\max}$ is calculated substituting V_{max} in Manning's equation similar to what was done for obtaining $\theta_{\min}$ from Eq. 14. After the upper and lower slope bounds for all pipes were calculated, the vector of sewer design slopes [S] is also determined from Eq. 11.

Installation elevations: A set of pipe diameters, slopes and pump locations after the adaptive decoding gives a feasible design for the sewer network at hand. In this design, all the sewer constraints have been met except the minimum cover on pipes. This need can be easily supplied by placing the pipes in appropriate elevations with respect to the required minimum cover depth $C_{\min}$. For this purpose, the upstream branches (chord links) in the network are firstly considered so that their upstream end's cover is assigned to be $C_{\min}$ resulting in:

$$EU_i = GU_i - C_{\min} \tag{16}$$

where EU_i and GU_i = respectively, the crown and ground surface elevations at the upstream end of pipe i. On this basis, the downstream crown elevation ED_i is obtained from:

$$ED_i = EU_i - S_i \times L_i \tag{17}$$

in which L_i = length of pipe i. Now the required cover is checked at the downstream end such that if GD_i - ED_i < $C_{\min}$ then:

$$ED_i = GD_i - C_{\min} \tag{18}$$

Thereby:

$$EU_i = ED_i + L_i \times S_i \tag{19}$$

After assigning the installation elevations of upstream branches the downstream pipes are step by step taken into account checking if their upstream pipes have been entirely placed or not.

For pipe i if the pump (lift) station indicator P_i=1 it means that there is a pump at its upstream end. If so, the pipe elevations are obtained calling Eqs. 16–19. In other words, existence of a lift station in a pipe makes that pipe like an upstream branch in the network. Otherwise, if P_i=0, the pipe upstream crown is placed at the lowest level of its inlet pipes connected to its upstream manhole. The downstream crown elevation is then obtained referring to Eqs. 17–19. This procedure is followed until for all pipes the installation elevations where determined.

6 Evolution in the GA

The proposed decoding strategy functions as an operator in the GA which always results in feasible population. To get the least-cost design, GA starts with an initial population which is then decoded using the described adaptive strategy. The construction cost of each chromosome, design alternative, is evaluated calling Eq. 5. The population is sorted in ascending order so that the cheapest design goes to the top of the list. Chromosomes in the upper half are considered for reproduction and transferred into the mating pool. Using the cost-weighting method (Haupt and Haupt 2004), the parents are selected. Every two binary string parents are mated to produce two offsprings. For this purpose, several methods may be used which are for example the single or multiple crossover points (Yoon and Moon 2002) and uniform crossover scheme (Syswerda 1989; Haupt and Haupt 2004) where the last one is adopted here. Afterwards, the new offsprings are allocated in the population instead of the discarded chromosomes. Then, the mutation operator is called to randomly switch a few binary genes off or on. A variable mutation ratio is considered in this work which is linearly decreased from the beginning to the end. GA then creates the new generation which needs to be decoded and evaluated and this process is continued until reaching to a desired convergence.

The described adaptive GA for optimization of sewer networks is also schematically presented in Fig. 2 in form of a flow diagram.

7 Case Study

To show how the proposed approach works, a benchmark sewer network from the literature is considered to be optimized. This problem was originally introduced by Li and Matthew (1990). The network consisting of 79 pipes and 80 manholes is designed to collect the sewage flow of a 260-ha residential area (Fig. 3).

Table 1 presents the name, length and flow rate of pipes in the network as well as the surface ground elevations. All the pipes also have the same Manning's coefficient of 0.014. Table 2 shows the design criteria which form the problem constraints. The sewer network is optimized with respect to the specified construction costs presented in Table 3. This table is then used to define the problem cost function (Eq. 5). In this problem, there are 24 available commercial diameter sizes: 0.2, 0.25, 0.30, 0.35, 0.38, 0.40, 0.45, 0.50, 0.53, 0.60, 0.70, 0.80, 0.90, 1.00, 1.05, 1.20, 1.35, 1.40, 1.50, 1.60, 1.80, 2.00, 2.20, and 2.40 m which constitute the vector of commercial list [*DC*].

To start optimization, it is first important to decide about the algorithm's parameters. In stochastic metaheuristics like GA the procedure of optimization is greatly dependent on the random-based operators and settings. The population size, crossover method and mutation ratio are for example very crucial to the GA performance. These parameters cannot be explicitly determined since their effects are different in each special problem. To determine the GA parameters, in general, the user needs to pay special attention to the number of problem decision variables and constraints and relies on his/her experiences on the GA and the problem at hand. Some preliminary runs in context of a sensitivity analysis are also very

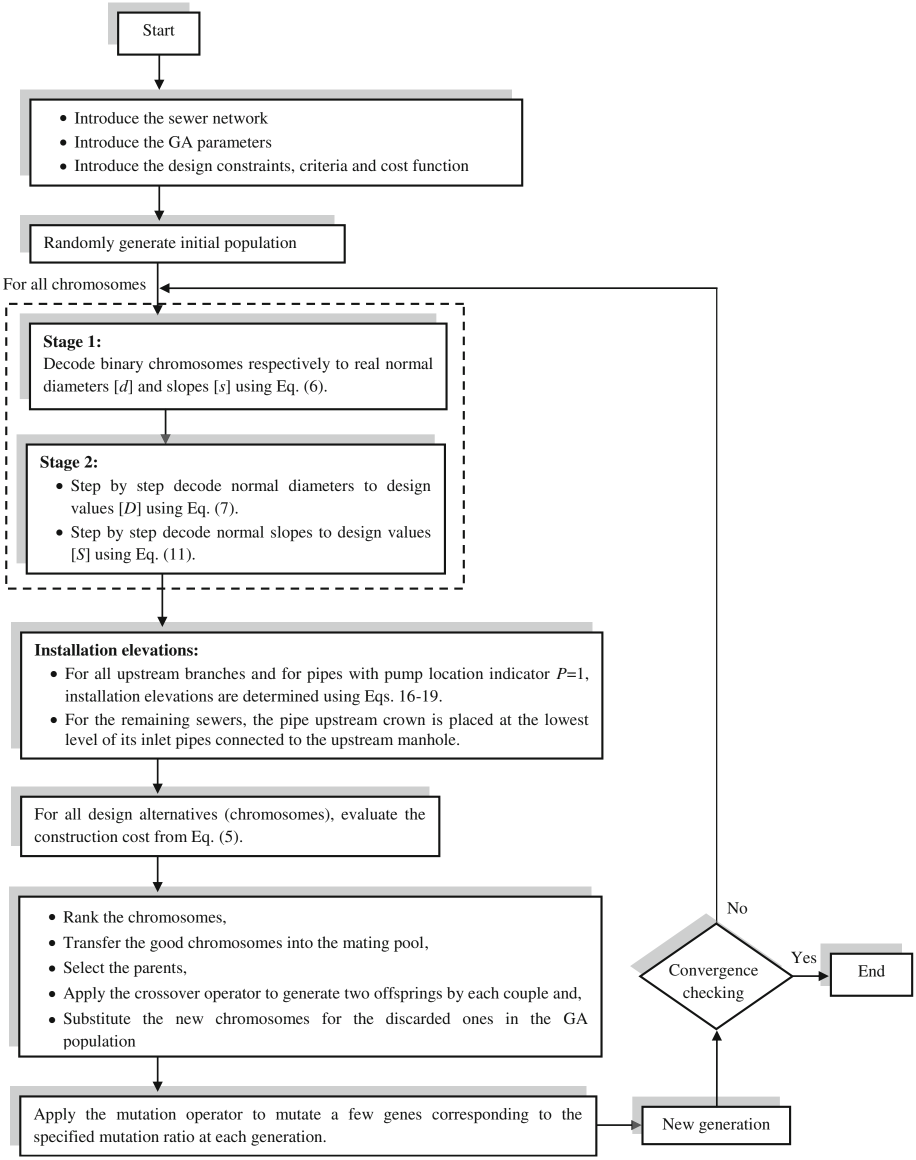

Fig. 2 Adaptive genetic algorithm for sewer networks design

helpful. In this work, with the aid of introduced adaptive decoding procedure GA in fact solves an unconstrained problem. This feature helps the GA freely search in the problem decision space and greatly reduces the unnecessary computations related to infeasible zones. From some initial trial-and-error runs it is also concluded that the adaptive constraint handling strategy somewhat decreases the sensitivity of GA to its random-based parameters like population size and mutation rate. In the simple GA used herein the uniform crossover method is adopted and considered fixed. A brief sensitivity analysis was done for population size and mutation ratio for only 100 generations. Figure 4(a) and (b) demonstrate some

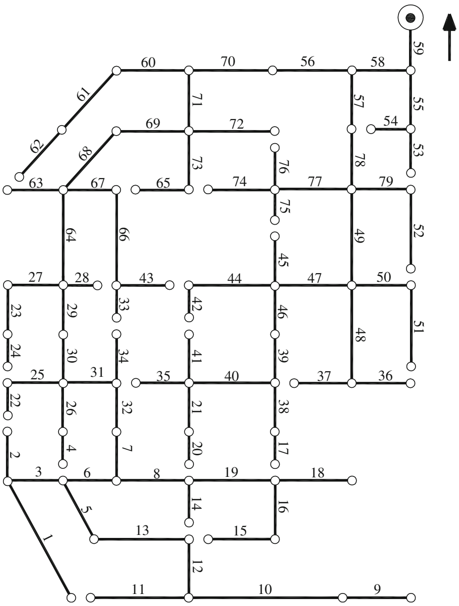

Fig. 3 Network layout of the case study (Li and Matthew 1990)

sample runs after the sensitivity analysis respectively for the population size and mutation ratio. As seen in Fig. 4(a), as the population size is increased the efficiency of the GA in the first 100 generations improves. However, it seems that this improvement becomes less significant after population size 120. In other words, the trend of optimization is not significantly different for the population sizes greater than 120, at least in the first 100 generations. Figure 4(b) also shows that lower mutation ratios are better suited to this problem. It is concluded from this sensitivity analysis that mutation rates less than 0.02 are more adequate. Consequently, for optimization of the sewer network the population size is considered to be consisting of 120 chromosomes. The mutation ratio is also considered to be linearly variable from 0.02 in the beginning to 0.001 in the last generation while the maximum number of generations is assigned to be 1000. Figure 5 illustrates the trend of cost function minimization through the GA generations. In the beginning, the best cost is 1.04e7 units. After only 254 generations the GA smoothly and relatively fast approaches to 1.84e6 units. This is a great speed for genetic algorithms applied to such large and complex problems. Afterwards, the GA slowly progresses and finally converges to 1.69e6 units at generation 505. As seen in Fig. 5, the GA was let continue until 1000 generations however, the best result did not change anymore after generation 505. For more information, the whole process took about 68 min for computations using a personal PC with an Intel Pentium 4 2.4 GHz CPU.

On the other side, since pumping facilities impose serious operational problems and costs to sewer systems, the experienced engineers often prefer not utilizing pumps in practice. In considering this issue, the problem was once more optimized without any pump in the system. In this condition, vector [P] is initially set to be null for all pipes. With the same settings for GA, the network was optimized in the absence of pump stations. Figure 6 shows the trend of cost function minimization in this situation which eventually converges to 1.84e6 units in generation 347. Following the style used by Pan and Kao (2009), Fig. 7 was prepared to demonstrate the optimized designs. Figure 7(a) shows the specifications of the

Table 1 Specifications of the example sewer network

Pipe	*GU* (m)	*GD* (m)	*L* (m)	*Q* (l/s)
1	2.50	2.30	360	5.87
2	2.20	2.30	350	7.69
3	2.30	2.50	290	19.07
4	2.50	2.40	270	9.92
5	2.60	2.50	260	31.57
6	2.50	2.90	220	50.09
7	2.90	2.50	240	95.97
8	2.85	2.90	275	48.59
9	2.80	2.70	240	5.87
10	2.70	2.60	300	9.72
11	2.50	2.60	490	4.86
12	2.60	2.70	250	17.52
13	2.70	2.60	300	25.63
14	2.70	2.85	310	2.23
15	2.70	2.60	240	13.03
16	2.60	2.80	230	20.08
17	2.80	2.60	200	7.69
18	2.80	2.80	190	8.91
19	2.80	2.85	380	38.52
20	2.85	2.60	250	3.24
21	2.60	2.45	200	5.87
22	2.25	2.20	300	6.07
23	2.10	2.10	280	11.72
24	2.20	2.10	360	6.07
25	2.20	2.40	350	12.10
26	2.40	2.40	230	18.56
27	2.10	2.20	230	15.04
28	2.00	2.00	250	2.63
29	2.40	2.00	260	142.18
30	2.40	2.40	310	135.41
31	2.50	2.40	300	108.32
32	2.50	2.50	180	100.23
33	2.40	2.20	190	9.92
34	2.40	2.50	260	7.08
35	2.50	2.45	320	10.52
36	2.30	2.35	290	4.45
37	2.40	2.35	325	5.67
38	2.60	2.40	200	11.33
39	2.40	2.20	210	44.16
40	2.45	2.40	370	29.80
41	2.25	2.45	260	2.63
42	2.25	1.95	230	4.66
43	1.95	2.00	225	2.02
44	1.95	2.00	350	10.73

Table 1 (continued)

Pipe	*GU* (m)	*GD* (m)	*L* (m)	*Q* (l/s)
45	2.05	2.00	180	3.64
46	2.20	2.00	230	53.21
47	2.00	1.95	320	68.50
48	2.35	1.95	440	28.69
49	1.95	2.00	290	106.98
50	1.90	1.95	310	18.56
51	2.30	1.90	440	10.25
52	1.90	2.00	350	5.06
53	2.00	2.10	310	4.05
54	2.10	2.10	260	7.89
55	2.10	2.20	300	15.22
56	2.20	2.25	350	208.37
57	2.10	2.25	230	140.62
58	2.25	2.20	280	328.16
59	2.20	2.20	500	337.77
60	2.20	2.20	180	12.85
61	2.20	2.20	230	9.72
62	2.20	2.20	230	4.66
63	2.20	2.10	270	1.42
64	2.00	2.10	250	154.43
65	2.00	2.10	260	6.48
66	2.00	2.00	140	13.59
67	2.00	2.10	270	18.04
68	2.10	2.10	280	172.55
69	2.10	2.20	280	180.36
70	2.20	2.20	350	203.94
71	2.20	2.20	270	192.34
72	2.10	2.20	230	7.49
73	2.10	2.20	300	8.91
74	2.10	2.10	320	3.24
75	2.05	2.10	150	3.04
76	2.10	2.10	300	10.73
77	2.10	2.00	290	21.72
78	2.00	2.10	280	135.65
79	2.00	2.00	310	13.03

obtained optimum design including pipe diameters and slopes as well as pipe buried depths. In this configuration, there is a pump station located at the upstream end of pipe 7. Figure 7 (b) also shows the no-pump design specifications.

Li and Matthew (1990) introduced and optimized this example using DDDP. They achieved an optimum design with 1.67e6 units of construction cost having a pump station at the upstream end of pipe 7. However, few numbers of constraints were not precisely met in that work. The examples are maximum proportional water depth in pipes 23, 60, 66 and

Table 2 Design criteria for the case study (Li and Matthew 1990)

Item name	Item value
Maximum velocity V_{max}	5.0 m/s
Minimum velocity V_{min}	0.7 m/s (if $D \leq 500$ mm, $Q > 15$ l/s)
	0.8 m/s (if $D > 500$ mm, $Q > 15$ l/s)
Minimum slope S_{min}	0.003 (if $Q \leq 15$ l/s)
Maximum proportional water depth $(h/D)_{max}$	0.6 (if $D \leq 300$ mm)
	0.7 (if D=350–450 mm)
	0.75 (if D=500–900 mm)
	0.8 (if $D \geq 1000$ mm)
Minimum cover depth C_{min}	1 m

79 (referring to Table 4 in Li and Matthew 1990). This happened probably because of the discrete nature of the applied method. Nevertheless, this issue does not decrease anything from the value of that work as well as the capability of DDDP in optimizing sewer systems.

Pan and Kao (2009) also developed a GA-QP model to optimize this example network. They found an optimum design with 1.74e6 units spending 299 min for calculations (using a PC with an Intel Pentium 4 2.0 GHz CPU). In that work, the population size and mutation probability were set to be 300 and 0.01, respectively and the optimization was terminated after about 1000 generations. There, all the constraints were satisfied and a pump station was located in the upstream end of pipe 68. They also applied GA and MGA methods for optimization of the problem without pump. An optimum no-pump design was then obtained with 1.91e6 cost units.

Comparing with the previous works manifests that the proposed adaptive GA is more successful in optimizing this problem as well as easier to implement. For the both designs, system with and without pump, the method resulted in better solutions in terms of the optimum design compared to GA-QP and satisfying all the constraints compared to DDDP. Figure 7 also helps the reader better compare the adaptive GA designs with the previous methods including DDDP, GA-QP and MGA which have similar figures in Pan and Kao (2009).

Table 3 Construction cost components (in Yuan) for the case study (Li and Matthew 1990)

For pipes, *CP*	*h*: Buried depth
$(4.27+93.59D^2+2.86D \times h+2.39h^2) \times L$	$D \leq 1$ m, $h \leq 3$ m
$(36.47+88.96D^2+8.70D \times h+1.78h^2) \times L$	$D \leq 1$ m, $h > 3$ m
$(20.50+149.27D^2-58.96D \times h+17.75h^2) \times L$	$D > 1$ m, $h \leq 4$ m
$(78.44+29.25D^2+31.80D \times h-2.32h^2) \times L$	$D > 1$ m, $h > 4$ m
For manholes, *CM*	
$136.67+166.19D^2+3.50D \times h+16.22h^2$	$D \leq 1$ m, $h \leq 3$ m
$132.67+790.94D^2-280.23D \times h+34.97h^2$	$D \leq 1$ m, $h > 3$ m
$209.04+57.53D^2+10.93D \times h+19.88h^2$	$D > 1$ m, $h \leq 4$ m
$210.66-113.04D^2+126.43D \times h-0.60h^2$	$D > 1$ m, $h > 4$ m
For pump stations, *CL*	
$270{,}021+316.42Q-0.1663Q^2$	Q (l/s)

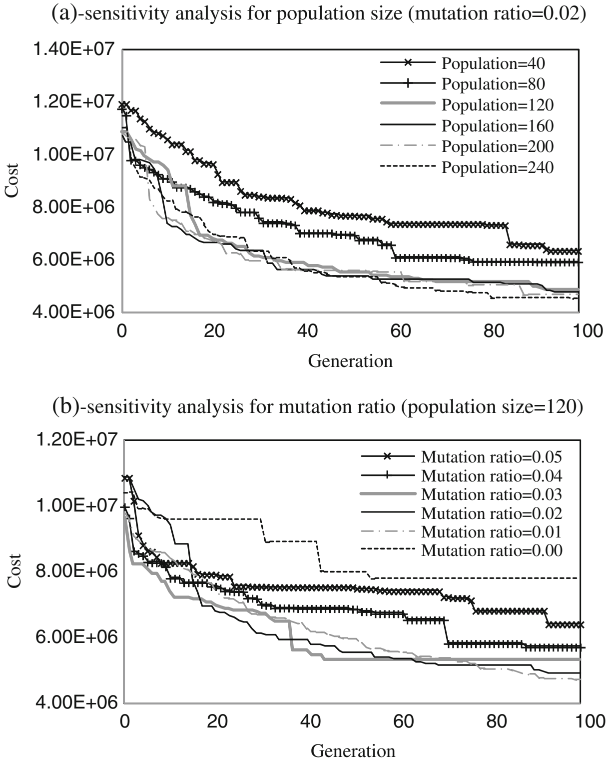

Fig. 4 Sensitivity analysis of GA for population size and mutation ratio

8 Conclusions

This paper introduces an adaptive genetic algorithm for optimization of sewer networks. The sewer design problem includes many complex constraints which are mostly nonlinear and discrete in nature. Handling such constraints is a major difficulty in designing sewer systems. For this purpose, a simple binary genetic algorithm was developed herein in which

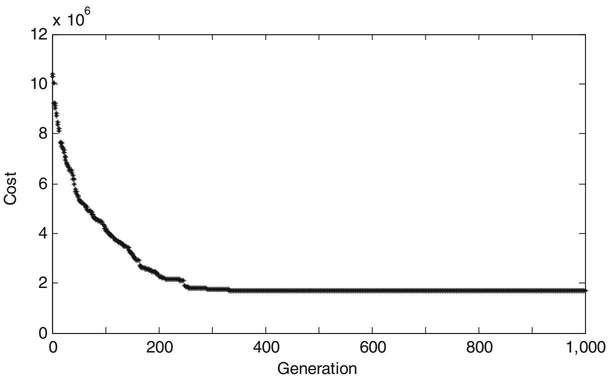

Fig. 5 Cost function minimization through the GA's generations

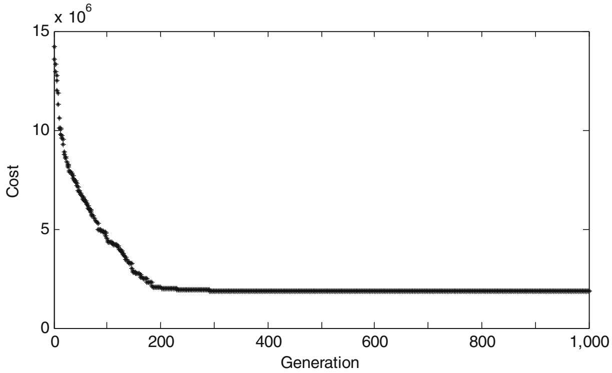

Fig. 6 Cost function minimization through the GA's generations in the absence of pump station

all the constraints are automatically satisfied. In the proposed scheme, binary chromosomes including pipe diameters and slopes and pump location indicators are randomly produced in

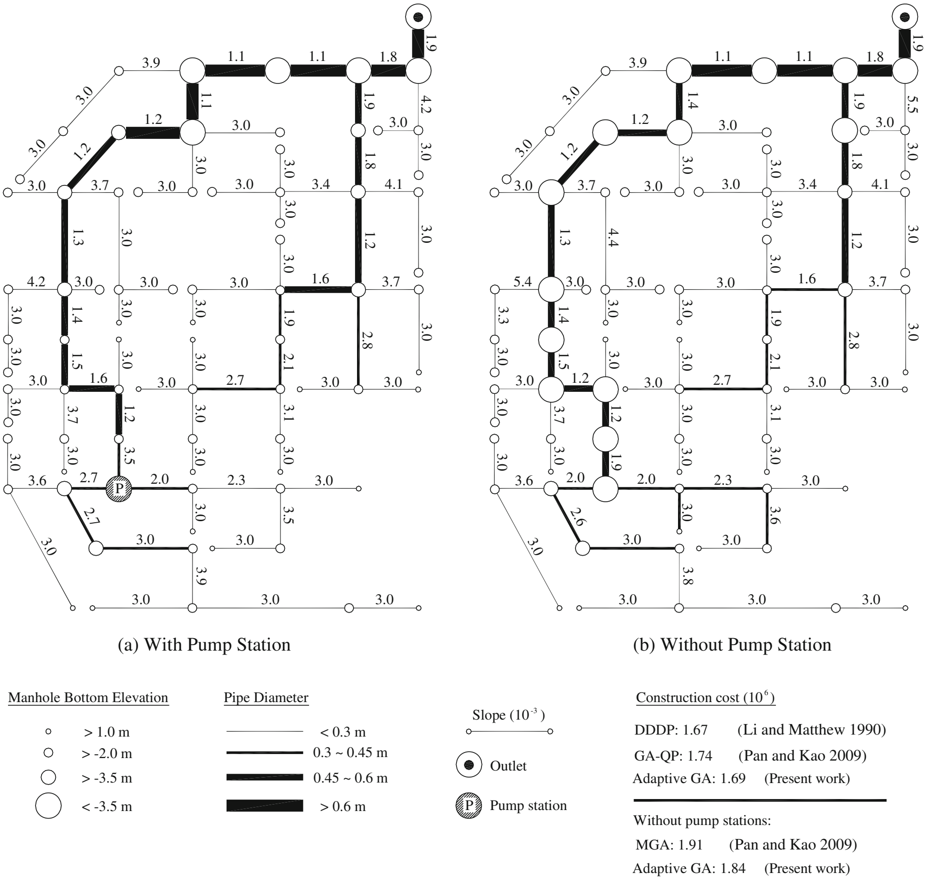

Fig. 7 Optimum designs of the case study

the beginning. By applying two successive decoding stages, the chromosomes are interpreted in feasible designs. Firstly, binary genes are decoded to normal real values. Afterwards, each design parameter is individually decoded subject to the problem constraints and free surface flow hydraulics. Using this method, all design criteria are systematically satisfied meaning that every randomly produced or treated chromosome during optimization becomes feasible. As a result, the problem of sewer network design becomes unconstrained. Using the adaptive GA, there is no need to discard or repair infeasible chromosomes or even applying penalty factors to the cost function. This helps the GA perform the optimization more efficiently in terms of speed and accuracy.

A benchmark sewer network was also taken into account. The example was optimized in two conditions, system with and without pump station. In the both cases, the results are satisfactory compared to the previously applied techniques. In conclusion, the method is found to be simple in concept and implementation as well as capable of solving large problems.

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