Optimization of Sewerage System Using Simulated Annealing

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Abstract- **Sewer networks are an important part of the infrastructure of any society. Since, the investment needed for construction and maintenance of these large scale networks is so huge and, thus any saving in the cost of these networks may result in considerable reduction of total construction cost. This study focuses on the issues of the design of sewer networks.In this paper, a new and powerful stochastic method, called Simulated Annealing (SA) is adopted for solving the sewer network optimization problem. Simulated Annealing (SA) is a probabilistic method proposed for finding the global minimum of a cost function that may possess several local minima. A sewer network is considered to show the Simulated Annealing algorithm performance, and the results are presented. The results show the capability of the proposed technique for optimally solving the problems of sewer networks.**

Keywords - Sewer network, Simulated Annealing, Optimal sewer design

I. INTRODUCTION

Sewerage or the wastewater system is the system of pipes used to collect and carry rain, wastewater and trade waste away for treatment and disposal. Sewage collection and disposal systems transport sewage through cities and other inhabited areas to sewage treatment plants to protect public health and prevent disease. The design of a sewerage system in general involves selection of a suitable combination of pipe sizes and slopes so as to ensure adequate capacity for peak flows and adequate self cleansing velocities at minimum flow. In a conventional design procedure, efforts are made to analyze several alternative systems (each meeting the physical and hydraulic requirements) and the least cost system is selected. Obviously, the outcome of such a procedure depends to a large extent on the designer experience and efforts. It is practically almost impossible to incorporate all feasible design alternatives, and an optimal solution is not necessarily reached. Only a resources to computer oriented optimal designing may be a solution.

Many optimization techniques have been applied and developed for the optimal design of sewer networks, such as linear programming [1, 2], nonlinear programming [3, 4] anddynamic programming [5–7]. Evolutionary strategies, such as genetic algorithms [8, 9], ant colony optimization algorithms [10, 11], cellular automata [12] and particle swarm optimization algorithms [13], have received significant consideration in sewer network design problems. Recently, Ostadrahimi et al. [14] used multi-swarm particle swarm optimization (MSPSO) approach to present a set of operation rules for a multi-reservoir system. Haghighi and Bakhshipour [15] developed an adaptive genetic algorithm. Therefore, every chromosome, consisting of sewer slopes, diameters, and pump indicators, is a feasible design. The adaptive decoding scheme is set up based on the sewer design criteria and open channel hydraulics. Using the adaptive GA, all the sewer system's constraints are systematically satisfied, and there is no need to discard or repair infeasible chromosomes or even apply penalty factors to the cost function. Moeini and Afshar [16] used tree growing algorithm (TGA) for efficiently solving the sewer network layouts out of the base network while the ACOA is used for optimally determining the cover depths of the constructed layout. Karovic and Mays [17] used simulated annealing within Microsoft Excel to sewer Ssystem design optimization.

In this paper, simulated annealing algorithm is applied to get optimal sewer network component sizes of a predetermined layout.

II. SEWER NETWORK DESIGN PROBLEM

A. Sewer Hydraulics

In circular sewer steady-state flow is described by the continuity principle (Q= VA) and Manning's equation which is

$$v = \frac{1}{n} R^{1/3} S^{1/2} \qquad (1)$$

where Q = sewage flow rate, V = velocity of sewage flow, A = cross-sectional flow area, R = hydraulic mean depth, n = Manning's coefficient and S = slope of the sewer. Common, partially full specifications for circular sewer sections are also determined from the following equations:

$$\frac{d}{D} = \frac{1}{2} \times \left(1 - \cos\frac{\theta}{2}\right) \quad (2)$$

$$r = \frac{D}{4}\left(\frac{\theta - \sin\theta}{\theta}\right) \quad (3)$$

$$a = \frac{D^2}{8}(\theta - \sin\theta) \quad (4)$$

D = sewer diameter, θ = the central angle in radian and (d/D) = proportional water depth, a = flow area while running partially full,r = hydraulic mean radius.

B. Design Constraints

For a given network, the optimal sewer design is defined as a set of pipe diameters, slopes and excavation depths which satisfies all the constraints. Typical constraints of sewer network design are:

1. Each pipe flow velocity should be greater than the minimum permissible velocityfor self cleaning capability and less than the maximum permissible velocity for preventing from scouring.
2. Flow depth ratio: wastewater depth ratio of the pipe should be less than 0.8.
3. Choosing pipe diameters from the commercial list.
4. Maintaining the minimum cover depth to avoid damage to thesewer line and adequate fall for house connections. The minimum cover depthof 0.9 m and maximum cover depth of 5.0 m has been adopted.
5. For each manhole, assigning the outlet pipe diameter equal to or greater than the upstream inlet pipes.

The optimal design of a sewer system for a given layout is to determine the sewer diameters, cover depths and sewer slopes of the network in order to minimize the total cost of the sewer system. The objective function can be stated as

$$\text{Minimize C} = \sum_{i=1}^{n}(\text{TC}_i + \text{PC}_i) \quad (5)$$

Where i = 1,…, n (total number of sewers), TCOSTi (total cost) = (Cost of sewer$_i$ + Cost of manhole$_i$ + Cost of earth work$_i$) and PCi = penalty cost (it is assigned if the design constraint is not satisfied).

III. SIMULATED ANNEALING (SA)

Simulated Annealing (SA) is a fairly new process for numerical optimization of many classes of problems. It is modeled after the centuries-old annealing process for metal and glass castings. Manufacturers anneal castings to make them tougher, by reducing their internal energy (McLaughlin, 1989) between Simulated Annealing and the physical process of annealing. In each case, a system of many variables is minimized. SA uses many steps in a random search to find the optimum of the system. Other random search algorithms are prone to selecting the first local optimum encountered. However, SA has a feature that helps it find the global optimum rather than a local optimum. The many steps required in SA are possible with modern computers, and the more capable computers become, the more useful SA will be.

A. Procedure of Simulated annealing algorithm

1. The first step in the algorithm is to choose a starting configuration and control parameter (analogous to temperature in physical annealing), then find the initial value of the objective function. While these choices of starting solution and temperature are unique to each application, SA is normally fairly insensitive to the starting conditions. In the application to structural optimization, this step establishes the initial physical characteristics of the structural components, ensures that all constraints are met, and determines the initial weight of the structure.

The term temperature is a holdover from the physical process of annealing, where it refers to the actual heat content of a casting. In simulated annealing, the temperature is a parameter that controls the probability of accepting a new solution that is "worse" than the old one. The higher the temperature, the greater the chance of accepting a "worse" solution. This probability of accepting a worse solution is the feature that allows SA to leave a local minimum and continue to search for the global minimum.

2. The second step in the algorithm is to randomly perturb the system. In explaining combinatorial optimization, Kirkpatrick, et.al. [18]described a random search method that accepts only lower values of the objective function at each iteration. It usually gets stuck in the local minimum closest to the starting point. This algorithm is often called the Greedy Algorithm because, in its "greed" to find any optimum, it will likely miss the global optimum and accept a local instead (McLaughlin, 1989:25). In 1985, Cerny [19] presented a Monte Carlo algorithm to find approximate solutions to the traveling salesman problem. "The algorithm generates randomly the permutations of the stations of the traveling salesman trip, with a probability depending on the length of the corresponding route”. This offers one method for generating random perturbations to a system. In structural optimization, this step corresponds to a random change in the physical dimension of one or more components.

3. The third step is to evaluate the new solution. The specific mechanics of this evaluation depend on the application. For structural optimization, this step determines the total weight of the structure with the new dimensions.

4. In the fourth step, accept or reject the new solution. If the new solution gives a lower value for the objective function, accept it. However, if the new solution gives a higher value, consider accepting it. This possibility of accepting the "worse" solution gives the SA algorithm the ability to leave a local optimum, and continue to search for the global optimum. This is the key feature that sets SA apart from other random search algorithms. From statistical mechanics, Kirkpatrick, et.al. [18] described the Metropolis procedure to overcome the Greedy Algorithm's problem of stalling at a local optimum. The Metropolis procedure from statistical mechanics provides a generalization of iterative improvement in which controlled uphill steps can also be incorporated in the search for a better solution [18]. This makes it possible for the algorithm to climb out of a local minimum and find a better local minimum, or the global minimum. Control for the uphill steps is given by the Boltzmann distribution:

$$P_r(E) = \frac{1}{Z(T)} \exp^{\left(\frac{-E}{K_B T}\right)} \quad (6)$$

Where, $P_r(E)$ is the probability of accepting the uphill step, $Z(T)$ is a normalizing factor depending on the assigned temperature(T), $E$is the average energy level, and $k_B$is the Boltzmann constant. The value of $k_B$is a natural constant, determined by experimentation, which adjusts the shape of the Boltzmann distribution to model the physical annealing process. It normally would not represent a valid constant in the SA process, but a different constant may be appropriate. For a given change in temperature, when the temperature is high, the probability of accepting an uphill step is high. As the temperature is reduced, the probability of accepting the uphill step is reduced.

5. The fifth step in the algorithm is to iterate at a given temperature and, when the system is at a stable average configuration for that temperature, reduces the temperature according to the annealing schedule. This schedule for reducing the temperature is critical to the success of either real or simulated annealing. According to Cerny experiments are done by careful annealing, first melting the substance, then lowering the temperature slowly, and spending a long time at temperatures in the vicinity of the freezing point. If this is not done, and the substance is allowed to get out of equilibrium, the resulting crystal will have many defects [19]. Quenching is the process of deliberately reducing the temperature quickly, without allowing the substance to reach equilibrium. This degenerates the SA algorithm to an ordinary random search like the Greedy Algorithm. In annealing, this process creates a brittle casting, but it is much quicker, and in some cases may be preferred to the slow annealing process. Quenching is not normally used in SA. To get the lowest possible cost with SA, the annealing schedule must allow the system to reach steady-state at each temperature. On the other hand, spending too much time at a given temperature wastes computer resources. So, the annealing schedule must allow the system to stabilize before changing temperature, and then change promptly.

The cooling schedule is often found by trial and error Brooks and Verdini [20]. However, Basu and Fraser [21] suggest that it may be cost effective to spend up to 80 percent of the total CPU time to establish the best cooling schedule. Collins et.al. [22] listed five different schemes for controlling the temperature, T:

- A constant value of T; T(t) = C
- An arithmetic function of T; T(t) = T(t - 1) – C
- A geometric function; T(t) = a(t)T(t - 1)
- An inverse; T(t) = C/(1 + ta)
- A logarithmic function; T(t) = C/In(1 + t)

6. The last step in the SA algorithm is to iterate until the stopping criteria is met. Several classes of stopping criteria can be used [22].

- In the simplest criteria, a fixed amount of CPU time is allocated, and the process stops when the time runs out [20].
- Another approach is to compare the value of the objective function at each iteration with the value at previous iterations. Under this criteria, stop when the function reaches a stable value for a certain number of iterations [20].
- If there is a certain target value of the function (a known or estimated minimum), stop when the configuration meets the target [20].
- When the algorithm is near the optimum the ratio of accepted configurations to total configurations will become very small. The algorithm can stop when this ratio reaches a predetermined value [23].

If none of the other criteria are met, stop when the temperature reaches a value near zero [22]. At this point the algorithm degenerates to a random search, and the cost of further annealing should be compared to the benefit that might be gained. When the correct stopping criteria are met, the algorithm will have a solution closer to the global optimum.

According to the above-mentioned steps, a possible structure of the Simulated Annealing algorithm is shown in fig. 1.

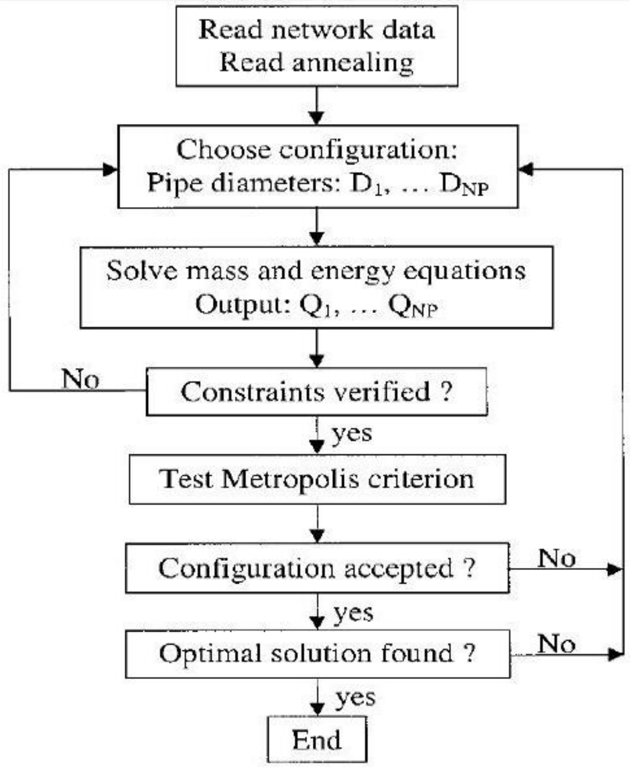

Fig. 1. Flow chart of Simulated Annealing Algorithm

IV. OPTIMIZATION OF SEWER NETWORK

The sewer network example (Banjaran sewer network, Laxmangarh, Rajasthan, India) is considered to check the above-proposed approach. The Banjaran sewer network as shown in Fig. 2 consists of 105 manholes, 104 pipes and STP is located at Node Number 0.

The following steps were used to optimize the component sizing of sewer system using the Simulated Annealing algorithm:

- Start with the first link (I=1) of the first iteration(ITN=1)

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- Calculate values of Hydraulic Mean Depth, Velocity, Depth of flow, and Discharge in partial flow condition.
- Calculate invert levels of upstream and downstream node of a particular link
- Calculate no of manholes, depth of excavation and earthwork.
- Calculate cost of sewer, cost of manholes and cost of earthwork.
- Calculate the total cost of the sewer network (TCOST)
- Add the respective penalty cost (PC) in TCOST where constraints are violated.
- Calculate feasible solution using SA
- Check solutions obtained are feasible or not.
- If feasible solution is not obtained repeat the process.
- If feasible solution is obtained, then take output.
- End.

The cost of pipe (RCC NP4 class), manhole and earth work was taken from theIntegrated schedule of Rates, RUIDP [24].

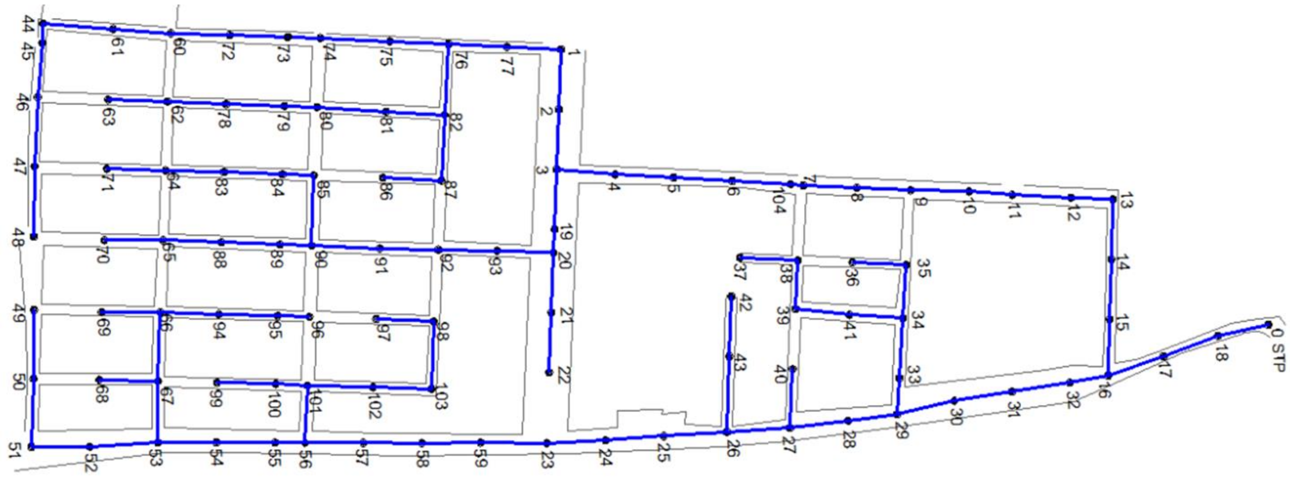

Fig. 2.Banjaran sewer network

V. RESULTS

The performance of the proposed Simulated Annealing procedure for optimization of the sewer system is now tested against Banjaran sewer network. The result exhibit a final total cost ofRs.8.505 × 10^6. 100000 evaluations were done for a system having 100 iterations for each evaluation. Then after accepting the higher as well as lower values of the function the global best solutions were achieved. The pipe diameter and slopes have been shown for the best solution. Accordingly the total cost of the sewerage system has been shown in the results. Table 1 shows the solution obtained by Simulated Annealing approach.

Table 1 Results of the Banjaran sewer network obtained by Simulated Annealing

Pipe no.	Node no.		Length (m)	Design flow (m/s)	Diameter (mm)	Slope (1 in)	v_p (m/s)	d/D	Cover depths (m)	
	Up	Down							Up	Down
24	23	22	30	0.0001	200	250	0.17	0.05	1.12	1.422
39	37	36	28	0.0002	200	250	0.19	0.06	1.426	1.12
41	38	39	20	0.0001	200	80	0.2	0.03	1.14	1.12
42	39	40	24	0.0001	200	250	0.18	0.05	1.434	1.12
44	40	42	28	0.0003	200	250	0.24	0.08	1.12	6.487
45	41	28	29	0.0001	200	250	0.16	0.04	1.12	1.338
46	42	35	28	0.0004	200	250	0.26	0.09	6.487	2.182
47	43	44	30	0.0001	200	60	0.26	0.03	1.12	1.184
48	44	27	38	0.0002	200	250	0.21	0.07	1.184	1.538
52	49	48	35	0.0001	200	250	0.17	0.05	1.12	1.489
54	50	51	35	0.0001	200	250	0.17	0.05	1.125	1.12
55	51	52	34	0.0002	200	250	0.21	0.07	1.12	1.343
56	52	53	30	0.0621	300	200	1.09	0.73	1.343	1.781
57	53	54	35	0.0622	300	200	1.09	0.73	1.781	1.969
69	64	63	30	0.0001	200	250	0.17	0.05	1.12	1.541
83	69	68	30	0.0001	200	200	0.18	0.05	1.12	1.126
80	70	67	30	0.0001	200	250	0.17	0.05	1.12	1.259
77	71	66	30	0.0001	200	250	0.17	0.05	1.12	1.373
74	72	65	30	0.0001	200	250	0.17	0.05	1.12	1.164
107	87	88	30	0.0001	200	250	0.16	0.05	1.12	1.415

102	88	83	33	0.0002	200	250	0.2	0.07	1.415	2.981
117	97	96	16	0.0002	200	250	0.21	0.07	1.12	1.593
120	98	99	30	0.0001	200	250	0.16	0.05	1.12	1.333
127	99	104	34	0.0002	200	250	0.21	0.07	1.333	1.297
122	100	101	30	0.0001	200	250	0.16	0.05	1.12	1.3
123	101	102	26	0.0002	200	250	0.2	0.06	1.3	1.362
126	104	103	30	0.0003	200	250	0.24	0.08	1.297	1.312
23	22	21	30	0.0002	200	250	0.21	0.07	1.422	1.701
36	36	35	27	0.0002	200	250	0.21	0.07	1.12	1.388
51	48	47	35	0.0002	200	250	0.21	0.07	1.489	1.832
71	63	79	30	0.0004	200	250	0.26	0.09	1.541	1.371
75	65	84	30	0.0004	200	250	0.26	0.09	1.164	1.498
78	66	89	30	0.0004	200	250	0.26	0.1	1.373	1.57
97	79	80	30	0.0005	200	250	0.27	0.1	1.519	1.12
98	80	81	17	0.0005	200	250	0.28	0.11	1.12	1.266
99	81	82	35	0.0007	200	250	0.31	0.13	1.266	1.493
101	82	83	30	0.0008	200	250	0.32	0.14	1.493	2.667
95	83	77	35	0.0011	200	250	0.36	0.16	2.981	2.849
103	84	85	30	0.0005	200	250	0.27	0.11	1.846	1.12
104	85	86	17	0.0005	200	250	0.28	0.11	1.12	1.238
106	86	91	35	0.0007	200	80	0.46	0.1	1.266	1.12
109	89	90	30	0.0005	200	80	0.4	0.08	1.57	1.3
110	90	91	18	0.0005	200	250	0.28	0.11	1.303	1.12
111	91	92	35	0.0015	200	70	0.6	0.13	1.12	1.624
113	92	93	30	0.0016	200	70	0.62	0.14	1.624	2.214
114	93	94	30	0.0017	200	70	0.63	0.14	2.214	2.919
115	94	21	29	0.0018	200	80	0.61	0.15	2.919	3.257
116	96	95	30	0.0003	200	250	0.22	0.08	1.593	1.637
124	103	102	33	0.0004	200	250	0.26	0.09	1.312	1.374
22	21	20	12	0.002	200	80	0.64	0.16	3.257	3.451
37	35	34	30	0.0007	200	250	0.31	0.13	2.182	2.433
50	47	46	27	0.0003	200	250	0.24	0.09	1.832	2.042
81	95	67	30	0.0003	200	250	0.25	0.09	1.637	1.855
125	102	57	29	0.0007	200	250	0.31	0.13	1.374	1.407
4	20	4	30	0.0021	200	80	0.64	0.16	3.451	3.853
38	34	30	18	0.0008	200	250	0.32	0.13	2.433	2.288
49	46	45	10	0.0011	200	250	0.36	0.16	2.042	2.131
79	67	68	34	0.0007	200	250	0.31	0.13	1.855	1.561
82	68	54	24	0.0011	200	250	0.35	0.16	1.561	1.819
68	45	62	36	0.0063	200	200	0.64	0.37	2.131	2.888
58	54	55	30	0.0634	300	200	1.1	0.75	1.969	1.858
59	55	56	30	0.0635	300	200	1.1	0.75	1.858	1.971
60	56	57	15	0.0635	300	200	1.1	0.75	1.971	1.913
61	57	58	30	0.0643	300	200	1.1	0.76	1.913	1.792
62	58	59	30	0.0644	300	200	1.1	0.76	1.792	2.257
63	59	60	30	0.0645	300	200	1.1	0.76	2.257	2.555
64	60	24	34	0.0646	300	200	1.1	0.76	2.555	2.77
65	62	61	30	0.0064	200	200	0.64	0.37	2.888	2.9
26	24	25	30	0.0647	300	200	1.1	0.76	2.77	2.93
27	25	26	30	0.0648	300	200	1.1	0.76	2.93	2.866
28	26	27	32	0.0649	300	200	1.1	0.76	2.866	2.366
29	27	28	32	0.0652	300	200	1.1	0.76	2.366	1.939
30	28	29	30	0.0654	300	200	1.1	0.77	1.939	2.19
31	29	30	25	0.0655	300	200	1.1	0.77	2.19	3.038
32	30	31	30	0.0663	300	200	1.1	0.78	3.038	3.197
33	31	32	30	0.0664	350	250	1.04	0.63	3.197	2.744
34	32	33	30	0.0665	350	250	1.04	0.63	2.744	2.02
35	33	17	20	0.0666	350	250	1.04	0.63	2.02	1.888
67	61	73	30	0.0067	200	200	0.65	0.38	2.9	2.97
89	73	74	30	0.0068	200	200	0.65	0.38	2.97	3.05
90	74	75	17	0.0068	200	250	0.6	0.41	3.05	2.379
91	75	76	35	0.0077	200	250	0.62	0.43	2.379	2.819
93	76	77	30	0.0078	200	250	0.62	0.43	2.819	3.817
94	77	78	30	0.0091	200	250	0.65	0.47	3.817	4.304

96	78	2	28	0.0092	200	250	0.65	0.47	4.304	3.154
1	2	3	30	0.0153	200	250	0.72	0.63	3.154	3.336
2	3	4	30	0.0154	200	250	0.72	0.64	3.336	2.991
3	4	5	30	0.0176	200	250	0.74	0.7	3.853	3.58
5	5	6	30	0.0177	200	250	0.74	0.7	3.58	3.593
6	6	7	30	0.0178	200	250	0.74	0.7	3.593	3.044
7	7	105	30	0.0179	200	250	0.74	0.71	3.044	3.132
128	105	8	7	0.0179	200	250	0.74	0.71	3.132	3.159
8	8	9	28	0.0192	200	250	0.75	0.74	3.159	3.595
10	9	10	28	0.0193	200	250	0.75	0.75	3.595	2.943
11	10	11	30	0.0195	200	250	0.75	0.75	2.943	3.105
13	11	12	22	0.0195	200	250	0.75	0.76	3.105	2.384
14	12	13	30	0.0266	250	250	0.83	0.62	2.384	2.078
15	13	14	21	0.0266	250	250	0.83	0.62	2.078	1.917
16	14	15	30	0.0267	250	250	0.83	0.62	1.917	1.737
17	15	16	30	0.0268	250	250	0.83	0.62	1.737	2.039
18	16	17	28	0.0269	250	250	0.83	0.62	2.039	2.601
19	17	18	30	0.0936	400	350	0.99	0.69	2.601	3.22
20	18	19	30	0.0936	400	350	0.99	0.69	3.22	3.531
21	19	1	26	0.0937	400	350	0.99	0.69	3.531	3.734

VI. CONCLUSION

The optimization technique adopted in this work proved to be successful in optimal designing of the sewerage network. In this study, the Simulated Annealing (SA) method of optimization a stochastic approach was applied to the problem of finding optimal pipe diameters and slopes for the conjunctive least-cost design and operation of a sewerage system network. Using the SA approach, the total cost of the sewer system was Rs. 8.505 × 10^6. The results indicated that the proposed approach is very promising and reliable, that must be taken as the key alternative to solve the problem of optimal design of the sewer network.

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