Environmental Engineering and Management Journal May 2019, Vol.18, No.5, 957-971
http://www.eemj.icpm.tuiasi.ro/; http://www.eemj.eu

"Gheorghe Asachi" Technical University of Iasi, Romania

ANT INTELLIGENT APPLIED TO SEWER NETWORK DESIGN OPTIMIZATION PROBLEM: USING FOUR DIFFERENT ALGORITHMS

Ramtin Moeini

Assistant professor, Department of Civil Engineering, University of Isfahan, Postal Code: 81746-73441, Isfahan, Iran
E-mail: r.moeini@eng.ui.ac.ir; Phone: +9831 37935293; Fax: +9831 36699515

Abstract

In this paper, four different kinds of the Ant Colony Optimization Algorithm (ACOA) are used to find optimal solution for sewer network design optimization problem proposing two different formulations for each of them. In both proposed formulations, the decision variables of the problem are cover depths of sewer network nodes. In the second formulation, the constrained version of ACOA is used to find optimal cover depths of the sewer network nodes. The constrained version of ACOA is used here to satisfy slope constraints explicitly leading to reduction of search space of the problem. The Ant System, Elitist Ant System, Elitist-Rank Ant System and Max-Min Ant System are used here to solve two benchmark test examples and the results are presented and compared with other available results. The results show the superiority of the Max-Min Ant System over than other ACOAs in which the trade-off between the two contradictory search characteristic of exploration and exploitation is managed better using this algorithm. Furthermore, best results are obtained with second proposed formulation in comparison with other available results in which they are shown the capability of the proposed formulation to find optimal solution for sewer network design optimization. In other words, the second formulation of Max-Min Ant System has been able to produce results 0.3% and 0.15% cheaper than those obtained by first formulation of Max-Min Ant System for the first and second benchmark test examples, respectively. Furthermore, the average solution cost value of second formulation of Max-Min Ant System is reduced 10.6% (8.1%), 0.43% (0.6%) and 0.34% (0.02%) in comparison with second formulation of Ant System, Elitist Ant System and Elitist-Rank Ant System for first (second) benchmark test examples, respectively.

Key words: Ant Colony Optimization Algorithm, constraint, optimal design, sewer network

Received: April, 2016; Revised final: July, 2016; Accepted: August, 2016; Published in final edited form: May 2019

1. Introduction

Nowadays, cost-saving is important issue in developing countries. The governments of these countries, therefore, do considerable efforts for cost-saving. Construction and developing infrastructures of cites are expensive task in which the governments want to do them with proper cost. Sewer network is one of these infrastructures in which it is designed to collect and transport the sewerage to treatment plant in order to protect human and environmental health. In order to design of least-cost sewer network, this problem should be formulated as an optimization problem in which it is not an easy task for engineers. In other words, solving this optimization problem is difficult due to the fact that it contains numerous alternative solutions and many complex hydraulic and engineering constraints.

Generally, sewer network design optimization problem is a highly constrained Mixed Integer Nonlinear Programming (MINLP) problem. Therefore, a group of researchers have been focused on it which can be classified as 1) Linear programming (LP), 2) Nonlinear programming (NLP), 3) Dynamic programming (DP) and 4) meta-heuristic algorithms (Moeini and Afshar, 2013a). Each of these methods has its own limitations such as limitations of calculating derivatives, requirement of an initial policy to start off the solution process and "curse of dimensionally" in which they limited the application of the conventional mathematical optimization and DP methods. Therefore, meta-heuristic algorithms have originally been proposed to overcome the limitations of the conventional optimization and DP methods (Moeini and Afshar, 2011).

Combinatorial optimization problems such as sewer network design optimization problem are NP-hard which cannot be solved optimality within proper computation time. These days, meta-heuristic algorithms have been proposed to solve these problems. The near-optimal solutions can be easily found in a relatively short time using meta-heuristic algorithms. Nowadays, many researchers have focused their attention on these algorithms and their applications in different fields of engineering problems. In other words, the use of meta-heuristics has widely increased due to the ability of finding very high quality solutions for combinatorial optimization problems in a reasonable time (Blum and Roli, 2003; Moeini and Afhar, 2013b).

Many different researches have been done for sewer network design optimization problem. Haestad (2004) and Guo et al. (2008) reviewed the researches developed in this field in the last 40 years. At first, Dajani and Hasti (1974) used LP to find least cost design for sewer network. Price (1978) used NLP to design least cost storm sewer network. Desher and Davis (1986) proposed a model named Sanitary Sewer Design for least cost design of a sanitary sewer network. Elimam et al. (1989) proposed a hybrid method to design large-scale storm sewer network by combining LP and a heuristic approach. Swamee (2001) designed an optimal sewer network using iterative application of the Lagrange-multiplier method. Walsh and Brown (1973), Templeman and Walter (1979), Yen et al. (1984), Botrous et al. (2000) and Diogo et al. (2000) designed a least-cost sewer network using DP. Gupta et al. (1983) used DP to find optimal cover depth and diameter combinations for all pipes of a complete gravity sewer system. DP was used by Kulkarni and Khanna (1985) to solve sewer network design optimization problem. Heaney et al. (1999) found least-cost solution for storm sewer network using Genetic Algorithm (GA). GA and Tabu Search (TS) were used by Liang et al. (2004) to solve sewer network design optimization problem. A new model named CASiNO was developed by Guo (2005) to solve sewer network design optimization problem using Cellular Automata (CA). Later, a hybrid method called CAGASiNO, combining CA and GA, was proposed by Guo et al. (2006) to solve sewer network design optimization problem. Afshar et al. (2006) used GA for storm sewer design optimization problem. A Partially Constrained Ant Colony Optimization Algorithm (PCACOA) was proposed by Afshar (2007) to solve storm sewer network design optimization problem using Max-Min Ant System (MMAS). Particle Swarm Optimization (PSO) algorithm was applied by Izquierdo et al. (2008) to find optimal solution for sewer network design optimization problem. Pan and Kao (2009) developed a hybrid model named GA-QP, combining GA with Quadratic Programming (QP), for sewer network design optimization problem. Afshar (2010) used Continuous Ant Colony Optimization (CACO) algorithm to solve storm sewer network design problem proposing constrained and unconstrained approaches. CA was used by Afshar et al. (2011) for sewer network design optimization problem. Haghighi and Bakhshipour (2012) used GA to find optimal solution for sewer network design optimization problem. Swamee and Sharma (2013) used LP to design an optimal sewer network. Karovic and Mays (2014) applied Simulated Annealing (SA) to solve sewer network design optimization problem. Liu et al. (2014) proposed a new method named SDE-GOBL (Self-adaptive Differential Evolution algorithm via Generalized Opposition-Based Learning) and applied to find optimal design of two sewer networks. PSO algorithm with new modification was used for optimally determine the sewer network component sizes of a predetermined layout by Navin and Mathur (2016). Finally, a new method was introduced by Safavi and Geranmehr (2016) for optimizing sewer network design using the Mixed-Integer Linear Programming (MILP) method for a given layout. Moeini (2017) used a new method named Arc based Ant Colony Optimization Algorithm (ABACOA) to solve sewer network design optimization problem. Moeini (2018) used The ACOA and CACOA and their constrained versions to optimal design of sewer network.

To evaluate the performance of ACOA to solve sewer design optimization problem, here, Ant System (AS), Elitist Ant System (ASelite), Elitist-Rank Ant System (ASrank) and Max-Min Ant System (MMAS) are used to solve this problem. Two different formulations are proposed for each of ACOAs denoted by suffix 1 and 2, respectively. In both formulations, the decision variables of the problem are the sewer network nodes cover depths. In the second formulation, the optimal cover depths of the sewer network nodes are found using the constrained version of ACOA in which the slope constraint is fully satisfied. The incremental building capability of ACOA is used here to propose the constrained version of the ACOA. In this algorithm, infeasible regions of the search space are removed from the problem search space. Proposed methods are used here to solve two benchmark test examples and the results are presented and compared with available results. In summary, this research has two significant advantages over pervious works. First, four different kinds of ACOAs are used here for sewer network design optimization to evaluate the performance of each this algorithms. Second and more important, each of pervious proposed methods has its own limitations in which these limitations are overcome here proposing different formulations. Here, proposed formulations lead to better results with lesser computational effort. The advantages of proposed algorithms and formulations are highlighted at section "Case studies and results" when proposed methods are used to solve two benchmark text examples. The layout of the paper, therefore, is as follows. In section 2, the formulation of sewer network design optimization problem is defined. The basic formulas and steps of ACOAs are also described in section 3. The methodology of solving the optimization problem of section 2 by proposing two different formulations of ACOAs are presented in section 4. Two benchmark test examples are solved in section 5 and the results are presented and compared with other available results to demonstrate the efficiency and accuracy of the proposed methods. Finally, some concluding remarks are addressed in section 6.

2. Mathematical formulation of Sewer Network Design

The sewer network which is consist of manholes, pipes, lifts and pumping stations and other appurtenances are designed to collect sewerages and transport them to treatment plants. Construction and developing sewer network is a quite complex expensive task. To design least-cost sewer network, therefore, this problem should be formulated as an optimization problem. By solving this optimization problem, the sewer network components such as pipe diameters, slopes, average cover depths, drops and pumping stations locations and heights can be optimally find subjected to the hydraulic and operational constraints.

In order to formulate the optimization problem, the objective function and constraints should be defined. Here, a sewer network with minimum construction cost should be designed and therefore the objective function can be formulated as Eq. (1).

$$\text{Minimize } C = \sum_{l=1}^{NP} L_l K_{pip}(d_l, E_l) + \sum_{m=1}^{NM} K_{man}(h_m) + \sum_{p=1}^{NPS} K_{pum}(q_p, h_p) + \sum_{d=1}^{ND} K_{drp}(h_d) \quad (1)$$

where, C= construction cost function of sewer network; L_l = length of pipe l; K_{pip} = the unit cost of sewer pipe provision and installation defined as a function of its diameter (d_l) and average cover depth (E_l); K_{man} = the construction cost of manhole as a function of manhole height (h_m); K_{pum} = the construction cost of pumping station as a function of pumping discharge (q_p) and height (h_p); K_{drp} = the construction cost of drop as a function of drop height (h_d); NP= total number of sewer pipes; NM = total number of manholes; NPS = total number of pumping stations; and ND = total number of drops.

In order to complete the formulation of the sewer network design optimization problem with a pre-specified layout, the problem constraints are also should be defined. Therefore, this problem is subject to the hydraulic, operational, and availability constraints as followings (Eqs. 2-9):

$$V_{min} \le V_l \le V_{max} \qquad \forall\, l = 1, \dots, NP \quad (2)$$

$$S_l \ge S_{min} \qquad \forall\, l = 1, \dots, NP \quad (3)$$

$$E_{min} \le E_l \le E_{max} \qquad \forall\, l = 1, \dots, NP \quad (4)$$

$$\beta_{min} \le \beta_l \le \beta_{max} \qquad \forall\, l = 1, \dots, NP \quad (5)$$

$$\beta_l = \left(\frac{y}{d}\right)_l \qquad \forall\, l = 1, \dots, NP \quad (6)$$

$$Q_l = \frac{1}{n} a_l r_l^{2/3} S_l^{1/2} \qquad \forall\, l = 1, \dots, NP \quad (7)$$

$$d_l \in \boldsymbol{D} \qquad \forall\, l = 1, \dots, NP \quad (8)$$

$$d_l \le \boldsymbol{d}_l \qquad \forall\, l = 1, \dots, NP \quad (9)$$

where, V_l = flow velocity of pipe l at the design flow; V_{max} = maximum allowable velocity of sewer flow; V_{min} = minimum allowable velocity of sewer flow; S_l = slope of the sewer pipe l; S_{min} = minimum sewer pipe slope; E_{min} = minimum allowable cover depth of sewer pipe; E_{max} = maximum allowable cover depth of sewer pipe; E_l = average cover depth of pipe l; d_l = diameter of sewer pipe l; y_l = sewer flow depth in pipe l; β_{max}= maximum allowable relative flow depth; β_{min} = minimum allowable relative flow depth; β_l = relative flow depth of pipe l; Q_l = the discharge of sewer pipe l; a_l = wetted cross section area of sewer pipe l at sewer flow depth of y_l; r_l = hydraulic radius of the sewer pipe l at sewer flow depth of y_l; S_l = slope of the sewer pipe l; n = Manning constant; $\boldsymbol{D}$ = discrete set of commercially available sewer pipe diameters assumed equal for all pipes of the network and $\boldsymbol{d}_l$= set of downstream pipe diameters of pipe l.

This optimization problem formulated with Eqs. (1) to (9) is a highly constrained MINLP which cannot be easily solved using conventional or heuristic methods due to the high number of constraints involved, non-convex search space, discrete and continues variables and non-linear objective function and some constraints. The complexity of the problem requires that an effective method is used to solve this optimization problem.

3. Ant colony optimization algorithm

Ant algorithm is kind of new meta-heuristic algorithm derived from the observation of real ants' foraging behaviour. Naturally, each ant deposits a chemical substance named pheromone on the ground which increases the probability that other ants will follow the same path. Based on this fact, real ants can find shortest path between food source and nest. This real ant's behaviour is exploited to proposed Ant Colony Optimization Algorithm (ACOA) which coordinates populations of artificial ants for solving computational problems. Starting from AS, a number of algorithms such as such as Ant Colony System (ACS), ASelite, ASrank and MMAS have been developed based on this real ant's behaviour and applied with considerable success to solve real-world engineering problems (Moeini and Afshar, 2009). Generally, many optimization problems have been solved using ACOA in the last 20 years which were reviewed by Ali et al. (2009), Ostfeld (2011), Stutzle et al. (2011) and Mohan and Baskaran (2012) in which reviewing them are not presented here.

Here, four different kinds of ACOA are used to solve sewer network design optimization problem. Fig. 1 shows the basic steps of solving optimization problem with ACOAs (Afshar and Moeini, 2008). It is worth noting that a transition rule is used by each ant to select proper option at each decision point i, which is denied as (Eq. 10):

$$p_{ij}(m,t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{j=1}^{J}[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}} \tag{10}$$

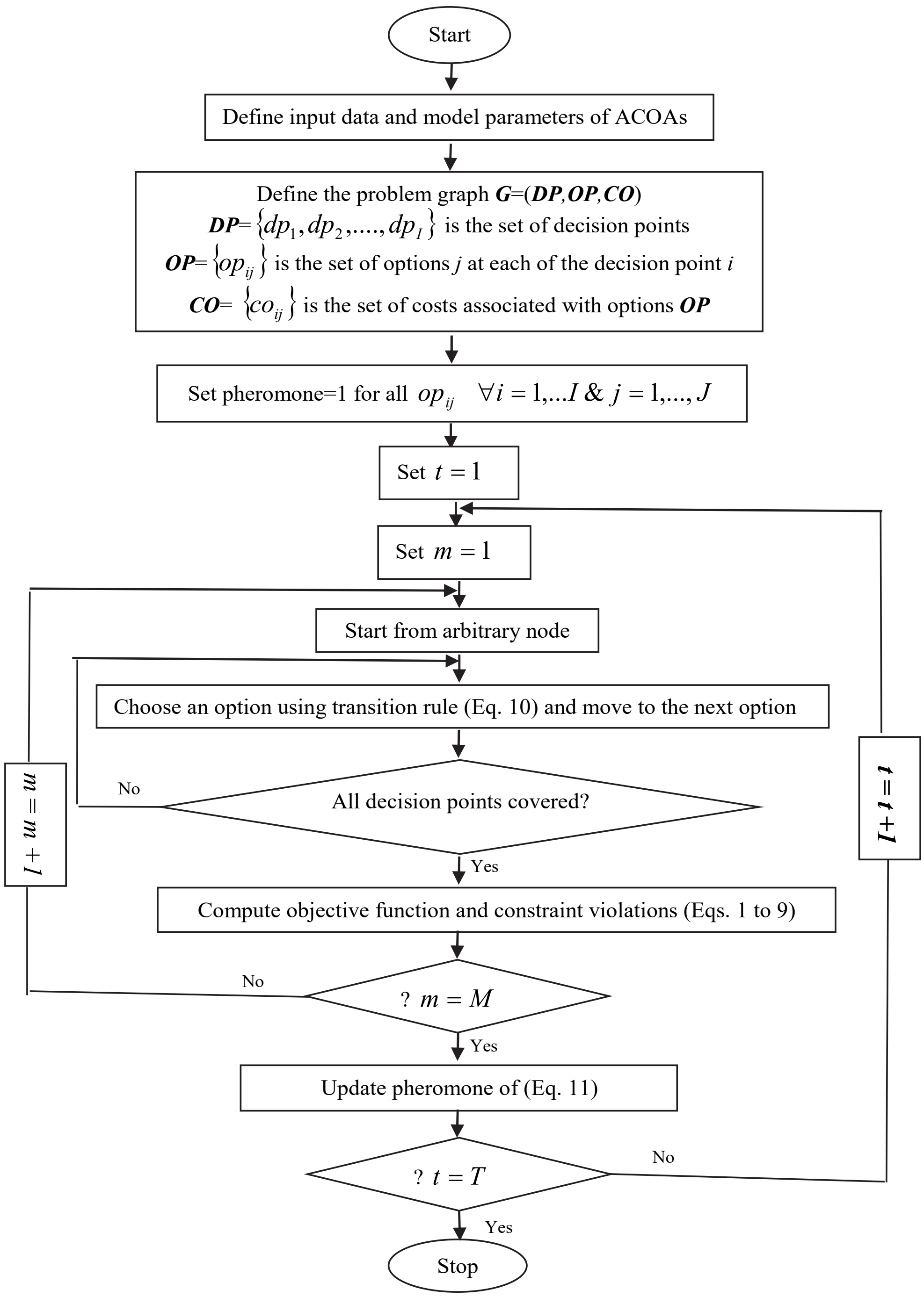

Fig. 1. Process of solution constructions in ACOAs (Moeini and Moulaei, 2018)

where, $p_{ij}(m,t)$ is the probability that the ant *m* selects option *j* of the *i*th decision point, op_{ij}, at iteration *t*; $\tau_{ij}(t)$ is the concentration of pheromone on option op_{ij} at iteration *t*; η_{ij} is the heuristic value of option op_{ij} and α and β are pheromone and heuristic sensitivity parameters, respectively.

Pheromone updating is the most important step of ACOAs for solving optimization problem in which different pheromone updating rules have been used for each of proposed ACOAs which are defined as Eqs. (11) to (15). In this Eqs., $\tau_{ij}(t+1)$ = the pheromone trail on op_{ij} at iteration *t+1*; $\tau_{ij}(t)$ = the pheromone concentration of on op_{ij} at iteration *t*; $\rho(0 \leq \rho \leq 1)$ = the coefficient representing pheromone evaporation; $\Delta\tau_{ij}^{ACOAs}$ = the pheromone concentration changes associated with op_{ij} defined as Eqs. (12) to (15); *R*= pheromone reward factor; $f(\varphi)^m$ = the solution cost produced by the ant *m*; σ = the number of best ants; $\Delta\tau_{ij}^{\sigma}$ = the pheromone concentration changes associated to σ best ants options; $f(\varphi)^k$ = the solution cost produced by the *k*th ant of best ranked ants, and $f(\varphi)^{best}$ = the solution cost produced by the best ant. It should be noted that, in MMAS, the pheromone is updated using only the cost of iteration-best ant.

Furthermore, the premature convergence to suboptimal solutions is a critical issue that can be experienced by all ant based algorithms. Therefore, Stutzle and Hoos (2000) developed MMAS algorithm to overcome this limitations. Provision of dynamically evolving bounds on the pheromone trail intensities is the fundamental basis of MMAS in which they are defined as Eqs. (16) and (17). In this Eqs., $\tau_{min}(t)$ and $\tau_{max}(t)$ = the lower and upper limit on the pheromone trail strength at iteration *t*, respectively; $f(\varphi)^{best}$ = the solution cost constructed by the best ant at each iteration; p_{best} = the probability that the best solution is constructed again; J_{avg}= the average number of options available at decision points of the problem; and *I*= the number of decision points.

It should be noted that, many advancements have been made on the AS to improve the decision policy operation and therefore four different kinds of ACOAs have been proposed. In other words, different manner have been proposed in which the decision policy incorporates new information to explore the problem search space. These developments try to manage the trade-off between the two exploration and exploitation characteristics.

$$Generalform: \quad \tau_{ij}(t+1) = \rho\tau_{ij}(t) + \Delta\tau_{ij}^{ACOAs}(t) \tag{11}$$

$$AS: \quad \Delta\tau_{ij}^{AS}(t) = \sum_{m=1}^{M} \Delta\tau_{ij}^{m}(t) = \begin{cases} \sum_{m=1}^{M} \dfrac{R}{f(\varphi)^m} & \text{if option } j \text{ is chosen by the ant } m \text{ at iteration } t \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

$$AS_{elite}: \Delta\tau_{ij}^{AS_{elite}}(t) = \sum_{m=1}^{M} \Delta\tau_{ij}^{m} + \sigma\Delta\tau_{ij}^{\sigma}(t) \tag{13}$$

$$AS_{rank}: \Delta\tau_{ij}^{AS}(t) = \begin{cases} \sum_{k=1}^{\sigma-1} \dfrac{(\sigma-k)R}{f(\varphi)^k} & \text{if option } j \text{ is chosen by } k\text{th ant of best ranked ant at iteration } t \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

$$MMAS: \Delta\tau_{ij}^{MMAS}(t) = \begin{cases} \dfrac{R}{f(\varphi)^{best}} & \text{if option } j \text{ is chosen by the best ant} \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

$$\tau_{max}(t) = \frac{1}{1-\rho}\frac{R}{f(\varphi)^{best}} \tag{16}$$

$$\tau_{min}(t) = \frac{\tau_{max}(t)(1-(p_{best})^{1/I})}{J_{avg} \cdot (p_{best})^{1/I}} \tag{17}$$

4. Methodology

The sewer network design optimization problem is solved here proposing two formulations for each of four different kinds of ACOAs. Generally, a graph should be defined for solving an optimization problem using ACOA. This graph consists of a set of nodes (representing decision points) and edges (representing options available at each decision points). Here, the decision variables of the problem are cover depths of sewer network nodes in both proposed formulations. In first formulation, denoted by suffix 1, the conventional application of ACOA and in second formulation, denoted by suffix 2, the constrained version of ACOA is used for decision variables determinations. The constrained version of ACOA is proposed here for the explicit enforcement of the problem constraints by limiting the ant's options to feasible ones at each decision point of the problem. This leads to limit the search space of the problem to feasible region and therefore will be shown to improved convergence characteristics and better results which are highlighted in the test example section.

In first formulation, the sewer network nodes are taken as decision points of the graph and the options available at each decision point are presented by all finite number of discrete nodal cover depths. Each ant starts its movement from arbitrary decision points and selects a cover depth from the set of available cover depths for each node. The problem graph representation for first formulation of ACOAs is shown in Fig. 2, where vertical lines represent the decision points, nodes, dashed horizontal small lines represent the components of nodal cover depths (j=1,…..J) at each decision point i (i=1,…..I), the dash lines represent potential solutions on the graph, and finally the bold lines represent a trial solution on the graph constructed by an arbitrary ant.

In second formulation, the sewer network nodes are also taken as decision points of the graph. However, the options available at each decision point are presented by some finite number of discrete nodal cover depths which are satisfied minimum slope constraint. In contrast with first formulation, in this formulation each ant starts its movement from inlets of sewer network and selects a cover depth from the tabu list which is consists of set of potential cover depths for each node satisfying minimum slope constraint. Furthermore, in the first formulation the number of options available at each decision point is fixed and equal to the number of the discrete cover depths obtained by discretisation nodal cover depth bounds. However, in the second formulation, the number of options available at each decision points is much smaller. The problem graph representation for second formulation of ACOAs is shown in Fig. 3, where vertical lines represent the decision points (sewer network nodes), small lines represent the components of nodal cover depths (j=1,…..J) at each decision point i (i=1,…..I) with the solid ones representing the infeasible and the dashed one representing feasible cover depths, the dash lines represent potential solutions on the graph, and finally the bold lines represent a trial solution on the graph constructed by an arbitrary ant.

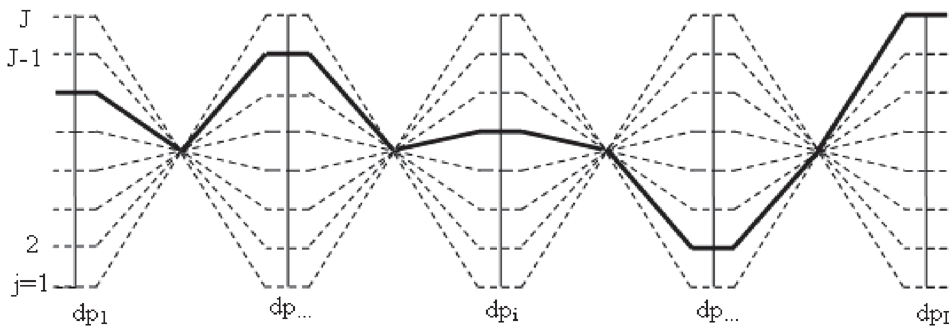

Fig. 2. Problem graph used for first formulation

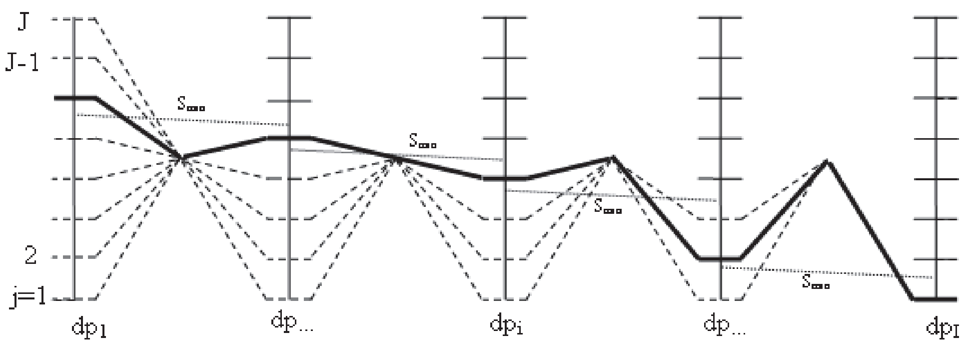

Fig. 3. Problem graph used for second formulation

By determining the nodal cover depths, nodal elevations and pipe slopes of sewer network in the both formulations, the remaining task is to determine the diameters of sewer network pipes as follow to complete the design process. By starting the design processes from upstream pipes, the smallest commercially available diameter fully satisfying constraints (2), (5), (6), (8) and (9) is taken as pipe diameter of each sewer network pipe.

It is worth noting that the two proposed formulations of MMAS are modified forms of Afshar (2007) formulations with minor corrections. These corrections are applied for pipe diameter determinations and methodology of constraints handling.

5. Case studies and results

In order to show the ability and performance of proposed methods to design optimal sewer network, two benchmark examples are applied. The first test example (*I*) as shown in Fig. 4 is applied by Mays and Wenzel (1976). This sewer network has 21 nodes and 20 pipes. Details of the network including nodal ground elevations, pipe lengths and design discharge of each pipe are given in Table 1. The problem constraints are as follow: maximum allowable flow velocity = 12 *fps* , minimum allowable flow velocity = 2 *fps* , maximum allowable relative follow depth = 0.9, minimum allowable relative follow depth = 0.1 and minimum allowable sewer pipe cover depth = 8 *ft*. For this test example, sewer network pipes have originally constant Manning coefficient. However, the sewer network pipes with variable Manning coefficient are assumed here in which they have the value of 0.013 at full condition. It is worth noting that the implicit hydraulic equations of simulation model at variable Manning coefficient are solved here using conventional iterative method. Commercial pipe diameters are presented in Table 3 and other problem data of this test example are presented in paper of Mays and Wenzel (1976). Here the Eq. (18) is used for pipe installation and manhole costs (Afshar et al., 2011; Mays and Wenzel, 1976).

The second test example (*II*) as shown in Fig. 5 is originally designed by Mansoury and Khanjani (1999). This sewer network has 21 nodes and 20 pipes. Details of the network including nodal ground elevations, pipe lengths and design discharge of each pipe are given in Table 2. The problem constraints are as follow: maximum allowable flow velocity = 3 m/s , minimum allowable flow velocity = 0.6 m/s , maximum allowable relative follow depth = 0.82, minimum allowable relative follow depth = 0.1 and minimum allowable sewer pipe cover depth = 2.45 *m*.

$$K_{pip} = \begin{cases} 10.98\, d_l + 0.8 E_l - 5.98 & \text{if } d_l \le 3' \text{ and } E_l \le 10' \\ 5.94\, d_l + 1.166\, E_l + 0.504\, d_l E_l - 9.64 & \text{if } d_l \le 3' \text{ and } E_l \ge 10' \\ 30.0 d_l + 4.9 E_l - 105.9 & \text{if } d_l > 3' \end{cases} \tag{18}$$

$$K_{man} = 250 + h_m^2$$

Table 1. First test example (*I*) data

Pipe No.	Node No. Up	Node No. Down	Ground elevation (ft) Up	Ground elevation (ft) Down	Design discharge (cfs)	Length (ft)
1	11	22	500	495	4	350
2	22	33	495	487	3	400
3	33	42	487	480	2	350
4	12	32	490	485	4	400
5	32	42	485	480	4	430
6	42	52	480	470	5	550
7	23	34	490	485	8	500
8	34	43	485	475	4	450
9	43	52	475	470	4	350
10	52	61	470	465	6	500
11	31	41	485	475	9	500
12	41	51	475	470	7	350
13	51	61	470	465	4	350
14	61	71	465	455	7	565
15	44	53	460	464	4	400
16	53	62	464	460	2	300
17	62	71	460	455	3	345
18	71	81	455	451	7	400
19	81	91	451	448	2	500
20	91	10	448	445	5	612

Table 2. Second test example (*II*) data

Pipe No.	*Node no.*		*Ground elevation (m)*		*Design discharge (m^3/s)*	*Length (m)*
	Up	*Down*	*Up*	*Down*		
1	1	4	74.59	73.66	27.9	260
2	2	9	70.7	69.9	54.9	300
3	3	15	73	71.50	21.1	400
4	4	5	73.66	72.1	30.4	460
5	5	6	72.1	71.99	32.4	260
6	6	7	71.19	69.85	34	300
7	7	8	69.85	68.24	36.6	450
8	8	12	68.24	67.82	38.7	400
9	9	10	69.9	69.3	56.2	270
10	10	11	69.3	68.4	58	310
11	11	12	68.4	67.28	59.6	440
12	12	13	67.28	66.22	96.7	470
13	13	14	66.22	65.82	101.2	350
14	14	20	65.82	65.42	104.7	340
15	15	16	71.5	70.1	26.4	400
16	16	17	70.1	68.6	30	400
17	17	18	68.6	66.8	31.9	500
18	18	19	66.8	66.1	40.3	400
19	19	20	66.1	65.42	44.6	590
20	20	21	65.42	64.5	165.9	320

Table 3. Candidate commercially pipe diameters of test examples

Test example	*Candidate commercially pipe diameters*
I	{12, 15, 18, 21, 24, 30, 36, 42, 48} (in)
II	{200, 250, 300, 400, 500, 600, 700} (mm)

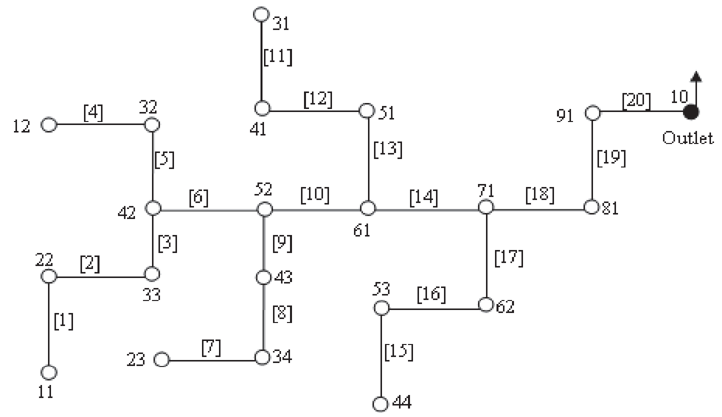

Fig. 4. Sewer network layout of first benchmark test example (*I*) (Moeini, 2018)

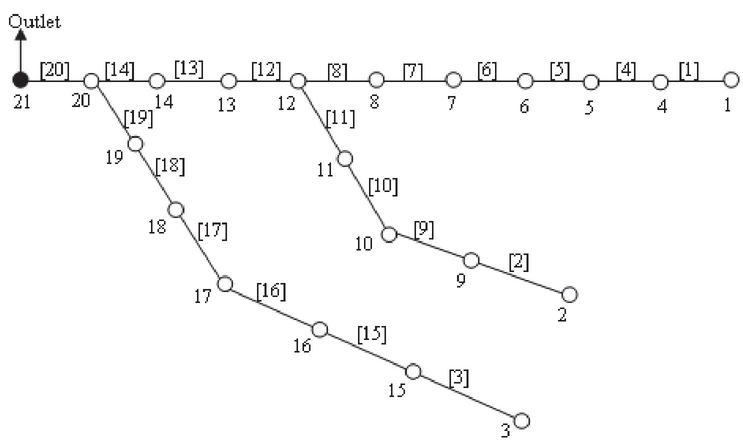

Fig. 5. Sewer network layout of second benchmark test example (*II*) (Moeini, 2018)

The sewer network pipes with constant Manning coefficient are assumed in which the value is equal 0.013. Commercial pipe diameters are presented in Table 3 and other problem data of this test example are presented in paper of Mansoury and Khanjani (1999). Here the following relation (Eq. 19) is used for pipe installation and manhole costs (Afshar et al., 2011; Mansoury and Khanjani, 1999):

$$K_p = 1.93 e^{3.43} d_l + 0.812 \overline{E}_l + 0.437 \overline{E}_l^{1.53} d_l \qquad (19)$$
$$K_m = 41.46 h_m$$

At first, a set of preliminary runs is done to find the proper values of each ACOA parameters. The proper parameters values of $\alpha = 1$ and $\rho = 0.95$ are obtained for all test examples. All the results presented hereafter are based on a uniform discretisation of the allowable range of cover depths into 40 intervals for all proposed formulations and test examples. It is worth noting that the number of best ant (σ) is 30 and 10 for first (*I*) and second (*II*) test examples, respectively. Furthermore, the value of p_{best} is 0.4 and 0.2 for first (*I*) and second (*II*) test examples, respectively. For all formulations proposed for each ACOAs, a colony size of 200 with maximum number of 1000 iterations amounting to maximum number of 200,000 function evaluations is used. It should be noted that in all proposed formulations no heuristic information can be defined and, therefore, the value of β=0.0 is used.

The results of 10 runs carried out using different randomly generated initial guess for the test examples along with the scaled standard deviation (SD) and the numbers of runs with final feasible solutions are presented in Table 4. Obtained results of Table 4 show that all measures of the quality of the final solutions are improved when using MMAS compared to other ACOAs. Furthermore, it is seen that second formulation of each ACOAs has been able to outperform first proposed formulation regarding the quality of the solution due to the fact that the search space of the problem is much smaller than those of first formulation by using constrained version of ACOA.

Tables 5 and 6 show the hydraulic characteristics for the optimal design of first (*I*) and second (*II*) test examples, respectively, using MMAS2. Figs 6 and 7 show convergence curves of the average solution costs obtained in ten runs using second formulation of different ACOAs for first (*I*) and second (*II*) test examples. These figures indicate superior performance of the MMAS compared to other algorithms in which the methodology of MMAS leads to lower cost final solution during the evolution process.

Table 7 compares the best results obtained by the proposed MMAS2 for both test examples with some other available results. At first, test example *I* was solved by Mays and Wenzel (1976) using Differential Dynamic Programming (DDP) and they reported optimal solution of 265775. Later, Robinson and Labadie (1981) and Miles and Heaney (1988) solve this problem using DP and a spreadsheet template respectively and the optimal solutions of 275218 and 245874 were reported. Afshar (2006, 2007, 2008 and 2010) proposed ACOA-AR (Adaptive Refinement process for ACOA), PCACOA, RPSO (Rebirthing Particle Swarm Optimization) and, also, CACOA methods to solve test example *I* and the optimal solutions of 241496, 242539, 242162 and 242119 were respectively reported requiring 29900, 13900, 30000 and 20000 function evaluations.

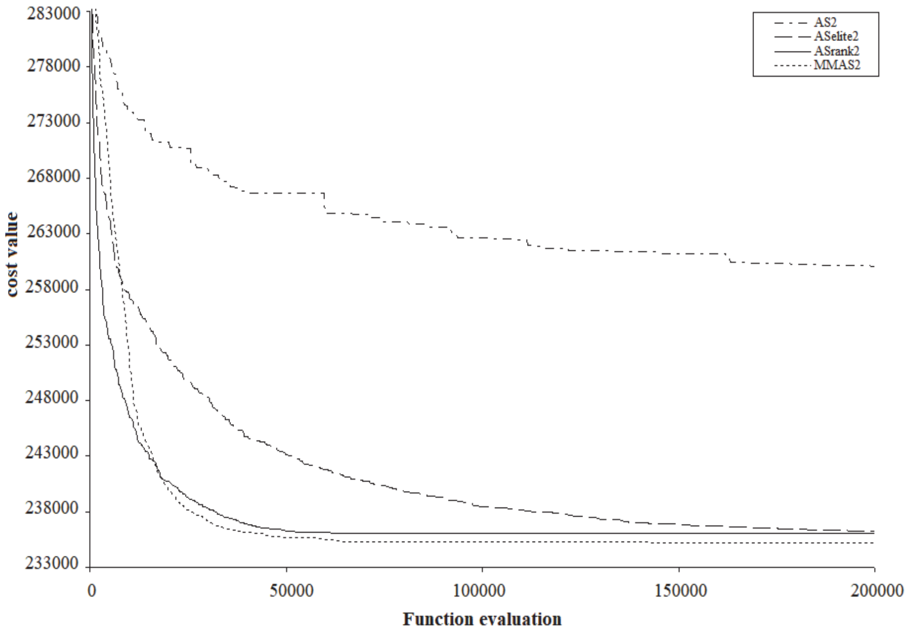

Fig. 6. Variation of average solution cost values of first test example (*I*) using second formulation of different ACOAs

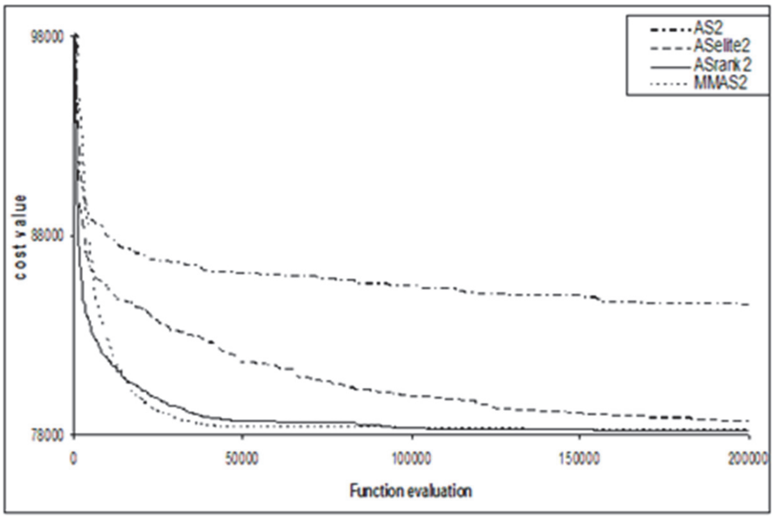

Fig. 7. Variation of average solution cost values of second test example (*II*) using second formulation of different ACOAs

Table 4. Maximum, minimum and average solution cost values over 10 runs obtained using proposed methods

Test example	*Formulations*	*Solution cost value*			*Scaled SD*	*No. of runs with final feasible solution*
		Minimum	*Maximum*	*Average*		
I	AS1	285381	291881	288305	0.0084	10
	AS2	254906	263601	260099	0.0079	10
	ASelite1	234510	241900	236911	0.0083	10
	ASelite2	233737	239233	236214	0.0074	10
	ASrank1	234309	241488	236386	0.0082	10
	ASrank2	233717	238158	236014	0.0062	10
	MMAS1	234309	239007	236185	0.0069	10
	MMAS2	233621	237578	235210	0.0051	10
II	AS1	88259.7	134989	108713	0.1187	10
	AS2	83551.2	85692.5	84534.3	0.0081	10
	ASelite1	83417.9	104409	93549.5	0.0737	10
	ASelite2	78102.1	79343.2	78664.3	0.0061	10
	ASrank1	78570.8	96597.4	81786.4	0.0646	10
	ASrank2	78102.1	78357.5	78217	0.0008	10
	MMAS1	78213.8	90982.5	80001.2	0.0487	10
	MMAS2	78102.1	78214.9	78202.7	0.0004	10

Table 5. Hydraulic characteristics of the optimal solution obtained by MMAS2 (test example *I*)

Pipe no.	*Node no.*		*Cover depths (ft)*		*Diameter (in)*	*Slope*	β	*V (ft/s)*
	up	*down*	*up*	*down*				
1	11	22	8	8	12	0.0143	0.8529	5.6054
2	22	33	8	8	15	0.02	0.7367	7.2236
3	33	42	8	8.3979	15	0.0211	0.8665	7.9664
4	12	32	8.7978	8	12	0.0105	0.6095	3.7401
5	32	42	8	8.3979	15	0.0126	0.6009	4.7502
6	42	52	8.3979	8	21	0.0175	0.6507	6.9766
7	23	34	8	9.3976	15	0.0128	0.6104	4.7914
8	34	43	9.3976	8	18	0.0191	0.7764	8.1517
9	43	52	8	8	21	0.0143	0.7886	7.8637
10	52	61	8	8.7978	30	0.0116	0.8958	9.4877
11	31	41	8	8	15	0.02	0.887	7.8204
12	41	51	8	8	21	0.0143	0.7886	7.8637
13	51	61	8	8.7978	21	0.0166	0.8834	8.8949
14	61	71	8.7978	8	36	0.0163	0.7816	11.9787
15	44	52	8	8.1979	12	0.0105	0.6095	3.7401
16	52	62	8.1979	8	15	0.0127	0.7756	5.8746
17	62	71	8	8	18	0.0145	0.7008	6.8034
18	71	81	8	8	42	0.01	0.8019	10.5203
19	81	91	8	8.1979	42	0.0064	0.6004	6.737
20	91	10	8.1979	9.9974	42	0.0078	0.6469	7.4259

Table 6. Hydraulic characteristics of the optimal solution obtained by MMAS2 (test example *II*)

Pipe no.	*Node no.*		*Cover depths (m)*		*Diameter (mm)*	*Slope*	β	*V (m/s)*
	up	*down*	*up*	*down*				
1	1	4	2.45	2.45	250	0.0036	0.667	0.8021
2	2	9	2.45	2.6436	300	0.0033	0.8077	0.8975
3	3	15	2.45	2.8372	200	0.0048	0.7679	0.8151
4	4	5	2.45	2.45	250	0.0034	0.7266	0.7957
5	5	6	2.45	2.45	250	0.0035	0.7565	0.8133
6	6	7	2.45	2.45	250	0.0045	0.7118	0.9098
7	7	8	2.45	2.6436	250	0.0041	0.7956	0.874
8	8	12	2.6436	2.45	300	0.0019	0.7517	0.679
9	9	10	2.6436	3.0308	300	0.0037	0.7867	0.9421
10	10	11	3.0308	2.45	400	0.0010	0.7199	0.5989
11	11	12	2.45	2.45	400	0.0025	0.5393	0.8624
12	12	13	2.45	2.45	400	0.0023	0.8002	0.897
13	13	14	2.45	3.0308	400	0.0028	0.7543	0.9951
14	14	20	3.0308	3.0308	500	0.0012	0.6818	0.7342
15	15	16	2.8372	2.45	250	0.0025	0.7295	0.6881
16	16	17	2.45	2.45	250	0.0038	0.6915	0.8285
17	17	18	2.45	2.45	250	0.0036	0.7376	0.8219
18	18	19	2.45	2.45	300	0.0018	0.8162	0.6524
19	19	20	2.45	3.0308	300	0.0022	0.8176	0.7209
20	20	21	3.0308	2.8372	500	0.0023	0.7573	1.0398

Table 7. Comparison the cost value and function evaluation obtained with different methods for both test examples

test example I										
Methods	**DDP (Mays and Wenzel, 1976)**	**DP (Robinson and Labadie, 1981)**	**Spreadsheet (Miles and Heaney, 1988)**	**ACOA-AR (Afshar, 2006)**	**PCACOA (Afshar, 2007)**	**RPSO (Afshar, 2008)**	**CACOA (Afshar, 2010)**	**CA (Afshar et al., 2011)**	**HPSO (Nafisi and Ahmadi, 2015)**	**MMAS2 (present work)**
Cost value	265775	275218	245874	241496	242539	242162	242119	253483	235699	233621
Function Evaluation	-----	-----	-----	29900	13900	30000	20000	50	80000	49200

test example II							
Methods	**GA & NLP (Mansouriand Khanjani, 1999)**	**NLP- BFGS (Setoodeh, 2004)**	**NLP- Fletcher-Reeves (Setoodeh, 2004)**	**GA (Setoodeh, 2004)**	**CA (Afshar et al., 2011)**	**HPSO (Nafisi and Ahmadi, 2015)**	**MMAS2 (present work)**
Cost value	83116	82732	81553	77736	80879	76342	78102.1
Function Evaluation	-----	------	------	100000	20	80000	37800

Furthermore, the proposed method of Afshar et al. (2011), CA, required 50 function evaluations to get the optimal solution of 253483 for text example *I*. Finally, this problem was solved using HPSO proposed by Nafisi and Ahmadi (2015) and the optimal solution of 235699 was reported requiring 80000 function evaluations. These results can be compared with the cost value of 233621 obtained using proposed MMAS2 for the test example *I* indicating the superiority of the proposed formulation with proper computational effort. Second test example (*II*) was solved at first by Mansouri and Khanjani (1999) using GA and NLP and they reported optimal solution of 83116. Setoodeh (2004) used NLP-BFGS, NLP-Fletcher-Reeves and GA to solve this test example and the optimal solutions of 82732, 81553 and 77736 were respectively reported. Furthermore, proposed method of Afshar et al. (2011), CA, required 20 function evaluations to get the optimal solution of 80879 for text example *II*. Finally, this problem was solved using HPSO proposed by Nafisi and Ahmadi (2015) and the optimal solution of 76342 was reported requiring 80000 function evaluations. These results can be compared with the cost value of 78102.1 obtained using proposed MMAS2 for this test example. Comparison of the results indicates the superiority of the proposed formulation to solve sewer network design optimization problem with proper computational effort. It should be noted that the proposed MMAS2 is produced near optimal solution of HPSO and GA of Setoodeh (2004) for text example *II* while it requires much less computational effort than these methods.

Finally, the claim that the search space created by constrained version of ACOA is smaller than original form of ACOA is supported by the two convergence curves shown in Figs 8 and 9 for average solution cost verse function evaluations for first (*I*) and second (*II*) test examples, respectively, using MMAS1 and MMAS2. These figures indicate superior performance of the constrained version of ACOA compared to original ACOA. First, the solution cost of MMAS2 remains lower than MMAS1 during the evolution process leading to lower cost final solution. Second, the MMAS2 solutions become feasible earlier than MMAS1 indicated by the fact that the MMAS2 convergence curve appear to the left of the other curves. This fact is more highlighted by the three convergence curves shown in Figs. 10, 11 and 12 for average solution cost verse function evaluations of first (*I*) test example using first and second formulations of AS, ASelite and ASrank, respectively.

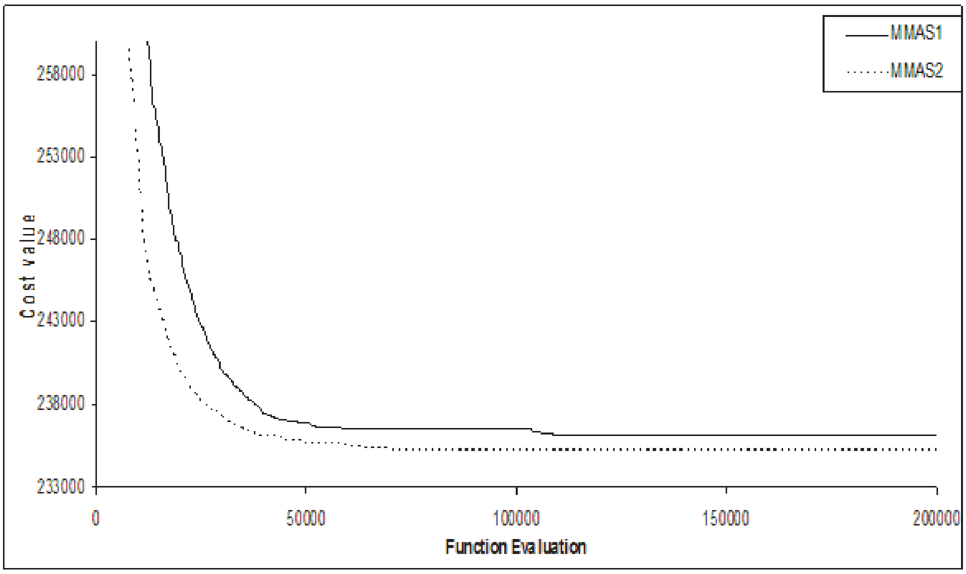

Fig. 8. Variation of average solution cost values of first test example (*I*) using MMAS1 and MMAS2

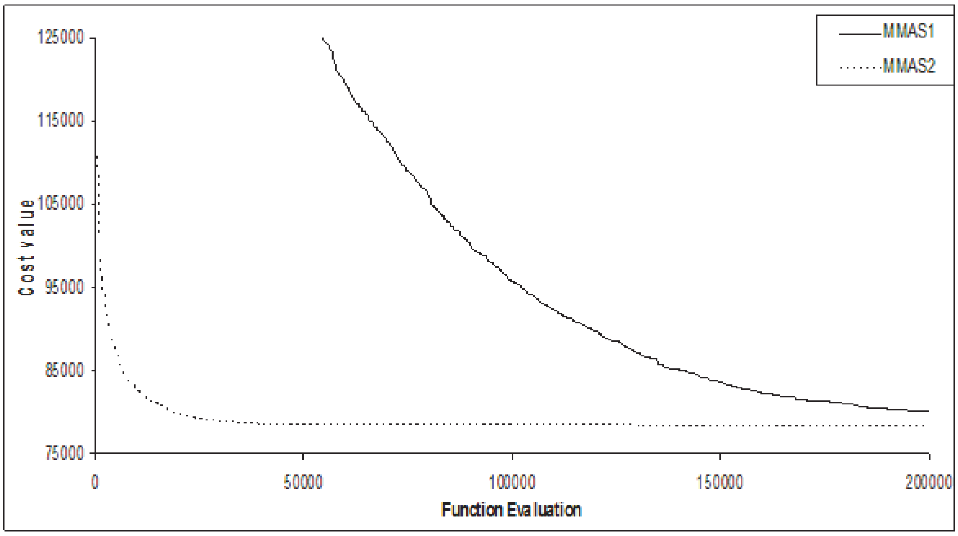

Fig. 9. Variation of average solution cost values of second test example (*II*) using MMAS1 and MMAS2

6. Conclusions

Here, Ant System (AS), Elitist Ant System (ASelite), Elitist-Rank Ant System (ASrank) and Max-Min Ant System (MMAS) were used to solve sewer network design optimization problem proposing two different formulations for each of them. These formulations were denoted by suffix 1 and 2, respectively. In both proposed formulations, the decision variables of the problem were nodal cover depths of sewer network. In addition, in the second formulation, the constrained version of ACOA was used to determine the nodal cover depths in which it was used to explicitly satisfy minimum slope constraint of sewer pipes. The proposed methods were used to solve two benchmark test examples and the results were presented and compared with other available results. The results indicated the capability of the proposed methods to effectively solve the sewer network design optimization problem.

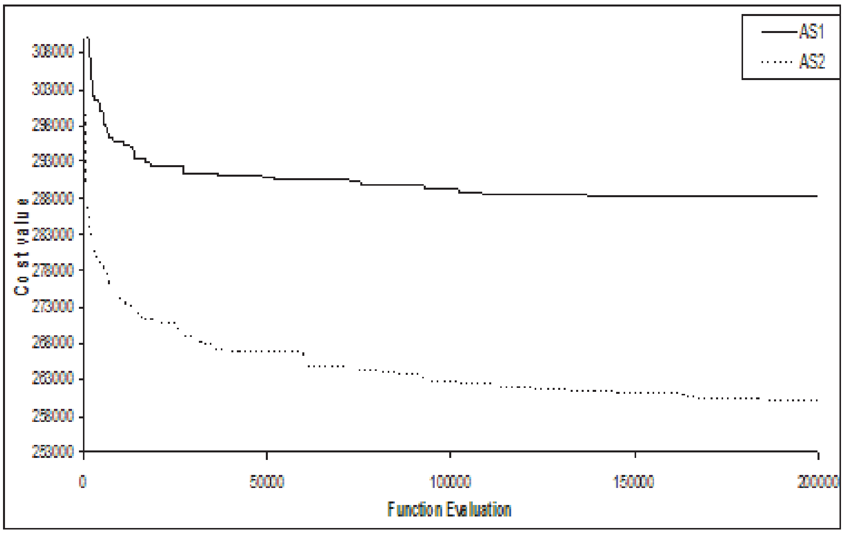

Fig. 10. Variation of average solution cost values of first test example (*I*) using AS1 and AS2

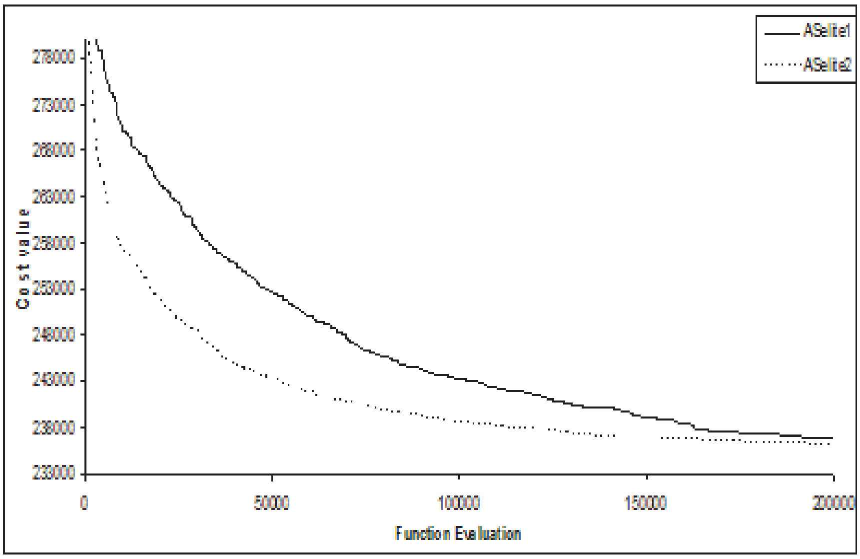

Fig. 11. Variation of average solution cost values of first test example (*I*) using ASelite1 and ASelite2

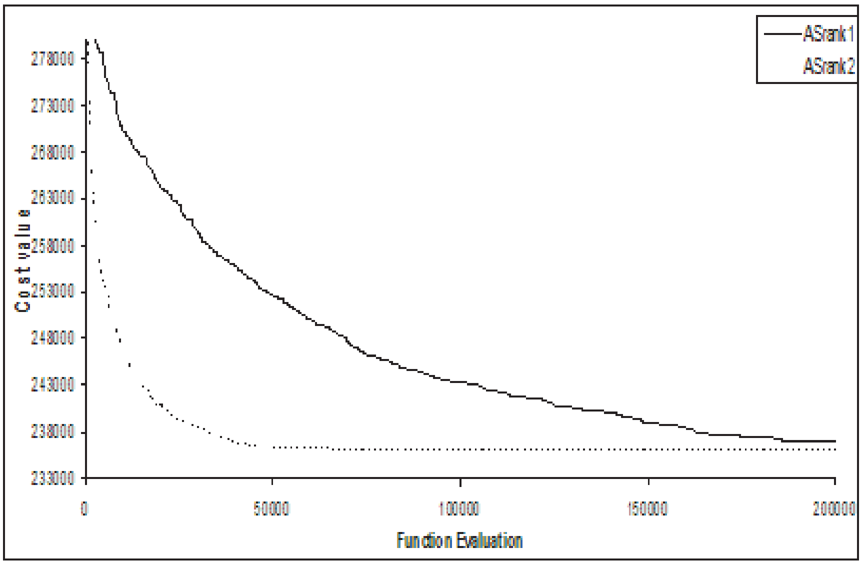

Fig. 12. Variation of average solution cost values of first test example (*I*) using ASrank1 and ASrank2

While all proposed methods showed good performance to solve the problems under consideration, the MMAS2 produced better results. In addition, the scaled standard deviation values of the solution showed that the proposed MMAS2 algorithm was less sensitive to the randomly generated initial guess solutions. In other words, comparing the results of AS2, ASelite2 and Asrank2 showed that the average solution cost values of MMAS2 were decreased 10.6% (8.1%), 0.43% (0.6%) and 0.34% (0.02%) that of related values, for first (second) benchmark test examples, respectively. Furthermore, the results of MMAS2 were 0.3% and 0.15% smaller than results of MMAS1 for the first and second benchmark test examples, respectively.

References

Afshar M.H., (2006), Improving the efficiency of ant algorithms using adaptive refinement: application to storm water network design, *Advances in Water Resources*, **29**, 1371-82.

Afshar M.H., (2007), Partially constrained ant colony optimization algorithm for the solution of constrained optimization problems: Application to storm water network design, *Advances in Water Resources*, **30**, 954-965.

Afshar M.H., (2008), Rebirthing particle swarm optimization algorithm: application to storm sewer network design, *Canadian Journal of Civil Engineering*, **35**, 1120-1127.

Afshar M.H., (2010), A parameter free Continuous Ant Colony Optimization Algorithm for the optimal design of storm sewer networks: Constrained and unconstrained approach, *Advances in Engineering Software*, **41**, 188-195.

Afshar M.H., Moeini R., (2008), Partially and Fully Constrained Ant Algorithms for the Optimal Solution of Large Scale Reservoir Operation problems, *Journal Water Resource Management*, **22**, 1835-1857.

Afshar M.H., Afshar A., Marino M.A., Darbandi A.A.S., (2006), Hydrograph-based storm sewer design optimization by genetic algorithm, *Canadian Journal civil Engineering*, **33**, 310-325.

Afshar M.H., Shahidi M., Rohania M., Sargolzaei M., (2011), Application of cellular automata to sewer network optimization problems, *Scientia Iranica. Transactions A: Civil Engineering*, **18**, 304-312.

Ali M., Pant M., Abraham A., (2009), *A Hybrid Ant Colony Differential Evolution and Its Application to Water Resources Problems*, Proc. of the 2009 Nature & Biologically Inspired Computing World Congress, 1133-1138.

Blum C., Roli A., (2003), Meta-heuristics in combinatorial optimization: Overview and conceptual comparison, *ACM Computing Surveys*, **36**, 268-308.

Botrous A., El-Hattab I., Dahab M., (2000), *Design of Wastewater Collection Networks Using Dynamic Programming Optimization Technique*, Proc. Of the ASCE Nat. Conf. on Environmental and pipeline Engineering, Kansas City, MO, United States, American Society of Civil Engineers, 503-512.

Mohan B.C., Baskaran R., (2012), A survey: Ant Colony Optimization based recent research and implementation on several engineering domain, *Expert Systems with Applications*, **39**, 4618-4627.

Dajani J.S., Hasit Y., (1974), Capital cost minimization of drainage networks, *ASCE Journal of Environmental Engineering*, **100**, 325-337.

Desher D.P., Davis P.K., (1986), Designing sanitary sewers with microcomputers, *Journal of Environmental Engineering*, **112**, 993-1007.

Diogo A.F., Walters G.A., Sousa E.R., Graveto V.M., (2000), Three-dimensional optimization of urban drainage systems, *Computer Aided Civil Infrastructure Engineering*, **15**, 409-426.

Elimam A.A., Charalambous C., Ghobrial F.H., (1989), Optimum design of large sewer networks, *Journal of Environmental Engineering*, **115**, 1171-89.

Guo Y., (2005), *Sewer Network Optimal Design Based on Cellular Automata Principles*, Proc. of 2005 XXXI IAHR Congress, Seoul, Korea, 6582-6593.

Guo Y., Walters G., Savic D., (2008), *Optimal Design of Storm Sewer Networks: Past, Present and Future*, Proc. of 11th International Conference on Urban Drainage, Edinburgh, Scotland, UK, 1-10.

Guo Y., Walters G.A., Khu S.T., Keedwell E.C., (2006), *Optimal Design of Sewer Networks Using Hybrid Cellular Automata and Genetic Algorithm*, Proc. of IWA World Water Congress, Beijing, China.

Gupta A., Mehndiratta S.L., Khanna P., (1983), Gravity Waste Water Collection Systems Optimization, *ASCE Journal of Environmental Engineering*, **109**, 1195-1208.

Haestad, (2004), *Wastewater Collection System Modelling and Design*, Waterbury, Haestad methods.

Haghighi A., Bakhshipour A.E., (2012), Optimization of sewer networks using an adaptive genetic algorithm, *Water Resource Management*, **26**, 3441-3456.

Heaney J.P., Wright L.T., Sample D., Field R., Fan C.Y., (1999), *Innovative Methods for the Optimization of Gravity Storm Sewer Design*, Proc. the 8th international conference on urban storm drainage, Sydney, Australia, 1896-903.

Izquierdo J., Montalvo I., Perez R., Fuertes V.S., (2008), Design optimization of wastewater collection networks by PSO, *Computers and Mathematics with Applications*, **56**, 777-784.

Karovic O., Mays L.W., (2014), Sewer System Design Using Simulated Annealing in Excel, *Water Resource Management*, **28**, 4551-4565.

Kulkarni V.S., Khanna P., (1985), Pumped wastewater collection systems optimization, *ASCE Journal of Environmental Engineering*, **111**, 589-601.

Liang L.Y., Thompson R.G., Young D.M., (2004), Optimising the design of sewer networks using genetic algorithms and tabu search, *Engineering, Construction and Architectural Management*, **11**, 101-112.

Liu C., Han H., Wang C., Junfei Qiao J., (2014), *An Adaptive Differential Evolution Algorithm for Sewer Networks Design*, Proc. of 11th World Congress on Intelligent Control and Automation (WCICA 2014), Shenyang, China, 3577 - 3583.

Mansouri M.R., Khanjani M.J., (1999), Optimization of sewer system by the nonlinear programming, (In Persian), *Journal of Water and Wastewater*, **30**, 20-30.

Mays L.W., Wenzel H.G., (1976), Optimal design of multilevel branching sewer systems, *Water Resource Research*, **12**, 913-917.

Miles S.W., Heaney J.P., (1988), Better than optimal method for designing drainage systems, *Journal of Water Resources Planning and Management*, **114**, 477-499.

Moeini R., (2017), Arc Based Ant Colony Optmization Algoruthm tosolve sewer network design optimization problem. *Scientia Iranica. Transactions A: Civil Engineering*, **24**, 953-965.

Moeini R., (2018), Different hydraulic analysis conditions for sewer network design optimization problem using different evolutionary algorithms, *International Journal of Operational Research*,**33**,512-537.

Moeini R., Afshar M.H., (2009), Application of an Ant Colony Optimization Algorithm for optimal operation of reservoirs: A comparative study of three proposed formulations, *Scientia Iranica. Transactions A: Civil Engineering*, **16**, 273-285.

Moeini R., Afshar M.H., (2011), Arc-based constrained ant colony optimization algorithms for the optimal solution of hydropower reservoir operation problems, *Canadian Journal of Civil Engineering,***38**, 811-824.

Moeini R., Afshar M.H., (2013a), *Sewer Network Design Optimization Problem Using Ant Colony Optimization Algorithm and Tree Growing Algorithm*, Proc. of EVOLVE 2013, A Bridge between Probability, Set Oriented Numerics, and Evolutionary Computation IVAdvances in Intelligent Systems and Computing, Leiden, Netherlands, **227**, 91-105.

Moeini R., Afshar M.H., (2013b), Extension of the constrained ant colony optimization algorithms for the optimal operation of multi-reservoir systems, *Journal of Hydroinformatics*, **15**, 155-173.

Moeini R., Moulaei S.A.M., (2018), Simulation-optimization model for design of water distribution system using ant based algorithms, *The Journal of Engineering Research*, **15**, 42-60

Nafisi M., Ahmadi A., (2015), Sewer networks optimization by particle swarm optimization with abilities of fly-back mechanism and harmony memory (In Persian), *Journal of Water and Wastewater*, **94**, 76-87.

Navin P.K., Mathur Y.P., (2016), *Design Optimization of Sewer System Using Particle Swarm Optimization*, Proc.of fifth international conference on soft computing for problem solving, the series Advances in Intelligent Systems and Computing, Saharanpur, India, **437**, 173-182.

Ostfeld A., (2011), *Ant Colony Optimization for Water Resources Systems Analysis – Review and Challenges*, In: Ant Colony Optimization - Methods and Applications, , Published by InTech.

Pan T.C., Kao J.J., (2009), GA-QP Model to Optimize Sewer System Design, *ASCE journal of environmental engineering*, **135**, 17-24.

Price R.K., (1978), *Design of storm water sewers for minimum construction cost*, Proc. of 1st International Conference on Urban Strom Drainage, Southampton, United Kingdom, 636- 647.

Robinson D.K., Labadie J.W., (1981),*Optimal Design of Urban Storm Water Drainage System*, Int. Symposium on Urban Hydrology, Hydraulics, and Sediment Control, University of Kentucky, Lexington, KY, USA, 145-156.

Safavi H.R., Geranmehr M.A., (2016), Optimization of sewer networks using the mixed-integer linear programming, *Urban Water Journal*,**14**, 452-459.

Setoodeh M., (2004), *Optimal design of sewer networks*, M.S. Thesis, Iran University of Science and Technology.

Stutzle T., Hoos H.H., (2000), Max-Min Ant System, *Future Generation Computer Systems*, **16**, 889-9140.

Stutzle T., López-Ibáñez M., Dorigo M., (2011), *Concise Overview of Applications of Ant Colony Optimization*, Wiley Encyclopedia of Operations Research and Management Science, John Wiley & Sons Inc, 896-911.

Swamee P.K., (2001), Design of Sewer Line, *Journal of Environmental Engineering*, **127**, 776-781.

Swamee P.K., Shama A.K., (2013), Optimal design of a sewer line using Linear Programming, *Journal of Applied Mathematical Modelling*, **37**, 4430-4439.

Templeman A.B., Walters G.A., (1979), *Optimal design of storm water drainage networks for roads*, Proc. of Inst. of Civil Engineers, London, 573-587.

Walsh S., Brown L.C., (1973), Least cost method for sewer design, *Journal of Environmental Engineering Division*, **99**, 333-345.

Yen B.C., Cheng S.T., Jun B.H., Voohees M.L., Wenzel H.G., (1984), *Illinois least cost sewer system design model*, User's guide, Department of Civil Engineering, University of Texas at Austin.