Desalination and Water Treatment
www.deswater.com
doi: 10.5004/dwt.2020.25822

193 (2020) 321–334
July

Water distribution networks optimization using GA, SMPSO, and SHGAPSO algorithms based on engineering approach: a real case study

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Received 5 June 2019; Accepted 10 March 2020

ABSTRACT

In modern societies, water distribution networks (WDNs) play a significant role in maintaining the standards of the desired life quality. The previous research findings indicated that meta-heuristic algorithms are stunningly capable of choosing the optimal sizes from a set of commercially available diameters in order to minimize the investment cost of WDNs. However, these methods usually suffer from falling in local optima or highly computational efforts. Therefore, in this study, a hybrid method referred to as a simple hybrid of genetic algorithm and particle swarm optimization (SHGAPSO) has been employed for the first time which depends on genetic algorithm (GA) and simple modified particle swarm optimization (SMPSO). SHGAPSO is developed based on a very simple but efficient hybrid use of GA and SMPSO, and then It is implemented on a real-life WDNs in Iran. In addition, an innovative constraint, which is called head loss gradient, is introduced that could replace the maximum velocity constraint. The results demonstrate that the hybrid technique is quite superior, mitigates the weakness of these two methods, and consequently increases the total efficiency. The results also show that the network design cost using SHGAPSO method is reduced by about 11% and 6%, respectively, compared to the GA and SMPSO algorithms. Moreover, using the maximum head loss gradient constraint causes pressure uniformity and creates surplus pressure in the nodes to the minimum permissible pressure, thereby increases the network hydraulic reliability, and velocity uniformity decreases velocity and head loss gradient in the pipes and ultimately reduces energy loss in the network.

Keywords: GA; SMPSO; SHGAPSO; EPANET 2.0; Water distribution networks; Optimization; Head loss gradient constraint

1. Introduction

Water distribution network (WDN) is considered as one of the infrastructures that noticeably facilitate human activities. WDNs are concerned with a safe as well as reliable water supply. The ultimate goal of WDNs is to both provide the consumers with the amount of water demand at the desired level of quality and pressure from the source to the end-user. In practice, only a limited number of pipe diameters are commercially available and the dependency between pipe diameter and the cost involved is quite nonlinear. In addition to this, there is a further nonlinearity

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imposed by the energy equation to calculate the head loss and the water flow in pipes that are the basic components used in the hydraulic study. That numerous candidate configurations can be applied to a WDN which will impose further complication to the design optimization problem. Due to the fact that the water flow direction along a pipe is not fixed in looped networks, determining the optimal-cost design is even more difficult [1]. In that regard, the traditional approaches to optimally design a water network do not allow to reach the optimal or even near-optimal solution. That is why there are a considerable number of research efforts in literature dealing with the optimal design of water networks. For instance, Alperovits and Shamir [2] proposed designed a linear programming (LP) gradient method to cope with the aforementioned issues by modifying the problem into a linearized sub-problem. The same method has been used and improved by many other research studies [3–7], which utilized dynamic programming (DP), approach to obtain the least-cost design [8] and attempted to find an optimal cost design by integrating a gradient-based technique with a hydraulic analysis model KYPIPE [9].

However, such mathematical methods were seen as insufficient to reach the optimal design of WDNs [10,11]. It should be mentioned that most of the well-known mathematical methods are limited in the way that they do not guarantee reaching the global optimum as the optimal design of a WDN involves discrete variables. Therefore, these mathematical methods yield relatively optimal results. That is why simulation-based meta-heuristic algorithms have been lately applied to optimal designing of WDNs so as to compensate for the weaknesses of the conventional trial-and-error and mathematical approaches. A bunch of research efforts that tried to employ heuristic methods are as follows: Some researchers [12–15] used genetic algorithms (GAs) to optimally design a WDN. Maier et al. [16], Zecchin et al. [17], and Mora-Melia et al. [18], adopted shuffled frog-leaping algorithms and ant colony optimization, respectively. Moreover, shuffled complex evolution, tabu search, cross-entropy, scatter search [19–22] was applied by other researches. A particle swarm optimization (PSO) algorithm was employed by Montalvo et al. [23], Ezzeldin et al.[24], and Qi et al. [25] and a harmony search algorithm was applied by Geem [26,27] for the optimal cost design of WDNs. Bolognesi et al. [28] applied genetic heritage evolution by stochastic transmission, whereas Vasan and Simonovic [29] applied a differential evolution approach. Recently, Fallah et al. [30,31] investigated improved crow search algorithm and gravitational search algorithm optimal pipe dimensioning in WDNs.

Such metaheuristic algorithms have been used in various ways for the optimal design of WDNs and have provided more efficient designs than previous ones. When PSO and GA are used individually, they may be stuck at local minimums, and in addition, are computationally demanding. To overcome this issue, some researchers have attempted to hybridize these two algorithms in the hope of enhancing the outcome. The key reason for hybridization is to take advantage of the strengths of each individual technique while simultaneously overcoming its main limitations [32]. The basic idea is to overcome critical problems of these methods such as premature convergence (particles in PSO can get stuck in a poor region of the search space), memory loss (if an individual in GA is not selected, its information is lost), and the parameter tuning [33]. In fact, hybrid evolutionary systems based on GA and PSO have shown to outperform its individual components in a number of (constrained and unconstrained) optimization problems.

Recently, many research studies on how to best combine GA and PSO have been performed. Their research findings show that combining these two algorithms gives a better performance than standard versions of GA and PSO. For example, Juang [34] presented a new evolutionary algorithm based on a hybrid of GA and PSO to best design recurrent neural-fuzzy networks. In this algorithm, both GA's operators and PSO are iteratively involved to generate well-modified populations. Premalatha and Natarajan [35] presented three new strategies to properly combine GA with PSO, and implemented the resulting algorithm on three well-known objective functions from the literature. They found that the proposed hybrid model outperforms the results obtained by the original algorithms. Esmin and Matwin [36] introduced a hybrid algorithm referred to as hybrid particle swarm optimization algorithm that used the mutation operator of GA to improve the PSO algorithm.

Moghaddam et al. [37] adopted a simple modified particle swarm optimization (SMPSO) to optimize the design of WDNs by using SMPSO as a novel technique in order to iteratively decrease inertia weight proportional to simulation time so as to guide the search toward the globally optimal point. This algorithm was applied to three benchmark networks and the results indicate that a significant improvement in the performance of PSO could be achieved by decreasing inertia weight over the iterations.

Minaee et al. [38] were used the simple hybrid of genetic algorithm and particle swarm optimization (SHGAPSO) method along with GA and PSO algorithms for qualitative calibration of a real-life WDN to minimize the difference between observed chlorine concentrations at measurement points and the concentrations simulated by the EPANET 2.0 hydraulic-qualitative simulation model. The results show that the SHGAPSO method enhanced the performance of GA and PSO algorithms in the scenarios studied.

This paper aimed at removing the well-known GA and PSO algorithms limitations and applying the results of a new hybrid optimization algorithm to the real executive projects. To achieve this goal, it has been tried to apply all engineering views and judgments to the problem. This paper was applied to the SHGAPSO algorithm for WDNs optimization based on the engineering approach. The performance of the hybrid method is discussed by implementing it on a real-life WDN in Iran. From the engineering point of view, a new and quite applicable constraint, which is called head loss gradient, is proposed successfully, as will be verified when presenting the simulation results, replaces for the usual maximum velocity constraint in the pipes. The optimization program is first coded in MATLAB and then is linked to EPANET 2.0 as a hydraulic simulation.

2. Optimization model

The optimal design of a WDN is defined as finding the best combination of the system components and settings such as pipe size diameters, pump types, pump locations and maximum power, and reservoir storage volumes, that satisfy the network objectives in a way that hydraulic constraints such as continuity of flow and energy as well as flow and nodal pressure requirements or other constraints reflecting network-specific considerations could be met. In this article, the design of a WDN is formulated to minimize investment costs [Eq. (1)] in which the pipe diameters are the decision variables. Therefore:

$$\text{Minimize } F_{\text{obj}} = \sum_{i=1}^{n\text{pipe}} C_i\left(D_i\right) \times L_i \tag{1}$$

where D_i is the diameter of pipe i, L_i is the pipe length, $C(D_i)$ is the unit cost of pipe diameter D_i, and $n$pipe is the total number of pipes needed in the network.

The constraints of the problem are defined as follows:

Constraint 1: Nodal mass balance

Flow that enters and leaves a node should be equal:

$$q_j^{\text{in}} - \left(q_{\text{j}}^{\text{out}} + q_j\right) = 0 \qquad j = 1,2,3,\ldots,\text{nd} \tag{2}$$

where q_j^{in} is the flow entering from upstream pipes to node j; q_j^{out} is the flow to downstream pipes from node j; and q_j is the demand satisfied at the node j.

Constraint 2: Loop energy balance

Head loss summation associated with any loops in a WDN should be zero:

$$\sum_{k \in \text{Loop } l} \Delta H_k = 0, \forall l \in \text{nl} \tag{3}$$

where ΔH_k is the head loss in pipe k, and nl is the total number of loops in the system. The head loss in each pipe is the head difference between the receiving and ending nodes that can be calculated by using the Hazen–Williams equation:

$$\Delta H_k = H_{1,k} - H_{2,k} = \omega \frac{L_k}{C_k^{\alpha} D_k^{\beta}} Q_k^{\alpha}, \forall k \in n\text{pipe} \tag{4}$$

where $H_{1,k}$ and $H_{2,k}$ are the heads at the two ends of the pipe, ω is the numerical conversion constant of the equation (which depends on the units used), C_k is the roughness coefficient of pipe k, (which depends on the material), and α and β are the regression coefficients. Given that the EPANET 2.0 software has been used here to solve the equation, the values of ω, α, and β are 10.667, 1.852, and 4.871, respectively.

Constraint 3: Pressure at nodes

Pressure available at all the demand nodes should be greater than or at least equal to the minimum required level and also smaller than or equal to the maximum allowed level of pressure.

$$P_j^{\min} \le P_j \le P_j^{\max}, \quad j = 1,2,3,\ldots,\text{nd} \tag{5}$$

where P_j is the pressure available at node j; $P_j^{\min}$ is the minimum pressure required at node j; $P_j^{\max}$ is the maximum pressure allowed at node j; and nd is the number of demand nodes.

Constraint 4: Velocity at pipes

Velocity in each pipe must be within the permissible band. Therefore:

$$V_k^{\min} \le V_k \le V_k^{\max}, \quad k = 1,2,3,\ldots,\text{np} \tag{6}$$

where V_k is velocity in pipe k, and $V_k^{\min}$ and $V_k^{\max}$ are the minimum and maximum allowed velocities in each pipe, respectively. np is the total number of the pipes of the network.

Constraint 5: Available pipe diameters

Pipe diameters must be selected from the commercially available pipe sizes, which form a discrete set:

$$D_i \in \left\{\text{CD}_k\right\} \forall i \qquad k = 1,2,3,\ldots,\text{nc} \tag{7}$$

where, D_i is the diameter of pipe i; CD_k is the kth commercially available pipe size; and nc is the number of available pipe diameters.

Constraint 6: Maximum head loss gradient (an engineering approach)

The head loss gradient is considered as one of the basic factors in WDN design, which has been disregarded by most of the experts when analyzing a WDN. From the engineering perspective, it is not correct to consider the same maximum velocity for all pipes as they are of different diameters, particularly for those made of polyethylene, widely used in Iran's WDNs. The authors have figured if a WDN is designed in a way that velocities close to 2 m/s occur in small-diameter pipes, the pipes, and the fittings will be incapable of tolerating such high velocities, and there will definitely be some breakage or burst due to vibration.

Thus, to optimize the WDN understudy, a new constraint has been defined and used in this article. The constraint is responsible for the maximum head loss gradient in a 1 km length of a pipe. The proposed constraint replaces for the maximum velocity constraint defined by Eq. (8). Indeed, Eq. (8) is a different expression of Hazen–Williams equation [8]:

$$V_k = 0.894 C_k R_k^{0.63} S_k^{0.54} \qquad k = 1,2,3,\ldots,\text{np} \tag{8}$$

where V_k is the velocity in pipe k (m/s), C_k is the roughness coefficient of pipe k, R_k is the hydraulic radius of pipe k (m) for a full pipe of geometric diameter D that is $D/4$, and S is the friction head loss per unit length or the slope of the energy grade line in meters per meter that is equal to H_k/L_k and named the head loss gradient. The Eq. (8) can be rewritten as below:

$$V_k = 0.894 C_k \left(\frac{D}{4}\right)^{0.63} \left(\frac{H_k}{L_k}\right)^{0.54} \quad k = 1,2,3,\ldots,np \tag{9}$$

To apply this constraint to the problem formulation based on [Eq. (9)], if the maximum head loss gradient value (H_k/L_k) is assumed to be 8 m in a length of 1 km (1,000 m) in pipes with different diameters, the maximum velocity will also be reduced as diameter decreases. The Hazen–Williams roughness coefficient is assumed to be 135 for polyethylene pipes. Table 1 illustrates the maximum velocity for all commercially available polyethylene pipe diameters that have been used in this study. It should be noted that the velocity equal to 2 m/s is considered for the pipe of the largest diameter (Table 1, [Eq. (9)]). Based on practical experience, maximum head loss gradient constraint causes the resulting design to be more resilient against breakage.

Table 1 presents the maximum allowed velocity variations for different diameters when the maximum head loss gradient constraint is taken into consideration.

It should be mentioned that the conservation of mass and energy constraints are satisfied during the simulation with EPANET, and other constraints are added to the objective function as penalty functions [37].

3. Genetic algorithm

GA is an adaptive search algorithm that works based on the evolutionary ideas of natural selection and genetics [39,40]. The genetic algorithm includes three major operators, (1) selection, (2) crossover, and (3) mutation. It generates a random initial population (represented by a string of genes or chromosomes) within the search bounds. The fitness values of these candidate solutions are assigned proportionally to their pertinent objective function values. Based on fitness values, GA forms a mating pool using the selection operation. The selection process allows multiple copies of elite solutions in the mating pool by removing inferior solutions. This phase does not create any new population. Subsequently, GA performs crossover operations to generate a new population. In this phase, having randomly picked up two individuals from the mating pool, the crossover operator partly crosses them in order to generate two new offspring. However, to maintain some of the superior solutions that exist in the parent population, crossover operation will be carried out only when the crossover probability is satisfied. Mutation operation is responsible for maintaining the diversity of the solutions through locally altering the genes. The mutation is also allowed only when the mutation probability is met. For an effective search, a higher value of crossover probability and lower value of mutation probability should be meticulously regulated [39]. The genetic algorithm performs the selection, crossover, and mutation operation in an iterative way until it reaches the stopping criterion.

Table 1
Maximum allowable velocity variations calculated for different diameters

Diameter (mm)	Maximum velocity* (m/s)
76.6	0.7
93.8	0.8
106.6	0.86
136.4	1.01
170.6	1.16
191.8	1.25
213.2	1.33
238.8	1.43
268.6	1.54
302.8	1.66
341.2	1.79
403.8	2

*Computed velocity based on maximum headloss gradient constraint (length = 1,000 m, C_{HW} = 135, and H_k/L_k = 8 m/km).

4. Simple modified particle swarm optimization algorithm

PSO is a promising optimization technique proposed [41]. It models a set of potential solutions as a swarm of particles moving around in a virtual search space. A swarm with P particles is optimized in an N-dimensional search space. Each particle of i has a position $X_i^t = (x_{i1}, x_{i2},\ldots, x_{is})$ and the velocity $V_i^t = (v_{i1}, v_{i2},\ldots, v_{is})$ is at iteration t. Each particle keeps tracking its position vector *p*best for which it has achieved the best fitness function so far. Position vector *g*best which represents the best value of fitness function obtained by the particles so far is also remembered. The values of the fitness function for these particles are stored as well. The PSO concept consists of changing the velocity of each particle towards its *p*best and *g*best. Once the velocities are determined, the position vectors of the particles will be updated. At these updated positions, the fitness function is recalculated and position vectors *p*best and *g*best will be updated again. This process goes on until a stopping criterion is met. In PSO, the following equations are used which iteratively modify the particle velocities V_{ij}^t and positions X_{ij}^t at iteration t [37,42,43].

$$V_{ij}^{t+1} = wV_{ij}^t + c_1 r_1^t \left(p\text{best}(i,j) - X_{ij}^t \right) + c_2 r_2^t \left(g\text{best}(j) - X_{ij}^t \right) \tag{9}$$

$$X_{ij}^{t+1} = X_{ij}^t + V_{ij}^t \tag{10}$$

where i = (1, 2,..., P) and j = (1, 2,..., n), c_1 and c_2 are acceleration constants and r_1, r_2 are random numbers between (0 and 1). The position vector *g*best (globally best position) and *p*best (particles' best positions) are modified during each iteration. Finely tuning the parameters of c_1 and c_2 in Eq. (9) may result in faster convergence and keeping the algorithm away from local minima. To control the velocity change, Clerc [44] introduced the constriction factor into the standard PSO algorithm to ensure the convergence of the search. The role of the inertial weight w in Eq. (9) is to control the impact of the previous velocities on the current one. A large inertial weight facilitates global exploration (searching for new areas), while a small weight tends to facilitate local exploration. Hence, the selection of a suitable value for the inertial weight w usually reduces the number of iterations required to locate the optimum solution [45–47] recommending that ω change between (0.4 and 0.9) in the standard PSO algorithm.

Therefore, in this study, a simple modified PSO, known as SMPSO presented by Moghaddam et al. [37], is used.

SMPSO employs a reduction factor known as w_{damp} that is effective in improving the speed convergence of the algorithm. It is important to determine the appropriate value of w_{damp}, as it reduces w following a linear form in each iteration based on Eq. (11):

$$w^{t+1} = w^t \times w_{damp} \tag{11}$$

To manage any changes in the particles' velocities, the relevant upper and lower limits are defined as follows in the Eq. (12):

$$V_{min} \leq V \leq V_{max} \tag{12}$$

Here, V_{max} is calculated by:

$$V_{max} = 0.5 \times \left(X_{max} - X_{min} \right) \tag{13}$$

$$V_{min} = -V_{max} \tag{14}$$

In which, X_{max} and X_{min} are the maximum and minimum diameters and can be taken into consideration for each network.

5. SHGAPSO (simple hybrid PSO – GA model)

The advantages of SMPSO algorithm over GA include simplicity, intelligibility, and controllability of convergence rate. In GA, mutation rate and crossover probability are effective on the algorithm convergence, but cannot control the rate of convergence as easily as inertia factor in SMPSO does. The effect of an increase in the rate of convergence can be observed directly in SMPSO as the inertia factor decreases, but the major drawback of SMPSO is its premature convergence and getting stuck in locally optimal points [48]. To avoid this, the best position of the swarm should be changed iteratively, and to this end, diversity among the population members can be increased through the inclusion of the mutation and crossover operators of GA in SMPSO, so that the probability of falling into local optima will be reduced.

In SHGAPSO, the total number of iterations is first specified and then the algorithm is divided into two sub-algorithms namely GA and SMPSO. In the first step, GA provides SMPSO with the best population, sorted by cost in ascending order. This population is imposed on SMPSO as the best individual and the global experience for the whole population. Then, at the end of each iteration, SMPSO calculates the values for the best member of the population for all of them based on the information calculated by GA for each population. These steps continue in each iteration until either the termination conditions are met or the maximum number of iterations is reached [38]. Fig. 1 illustrates the SHGAPSO flowchart.

Finally, it worth mentioning that the method used in this study consists of two phases called optimization and simulation. Firstly, in the optimization phase, GA, SMPSO, and SHGAPSO algorithms calculate the selected solutions (commercial diameters selected for the network pipes). Then, these solutions are introduced to simulation phases

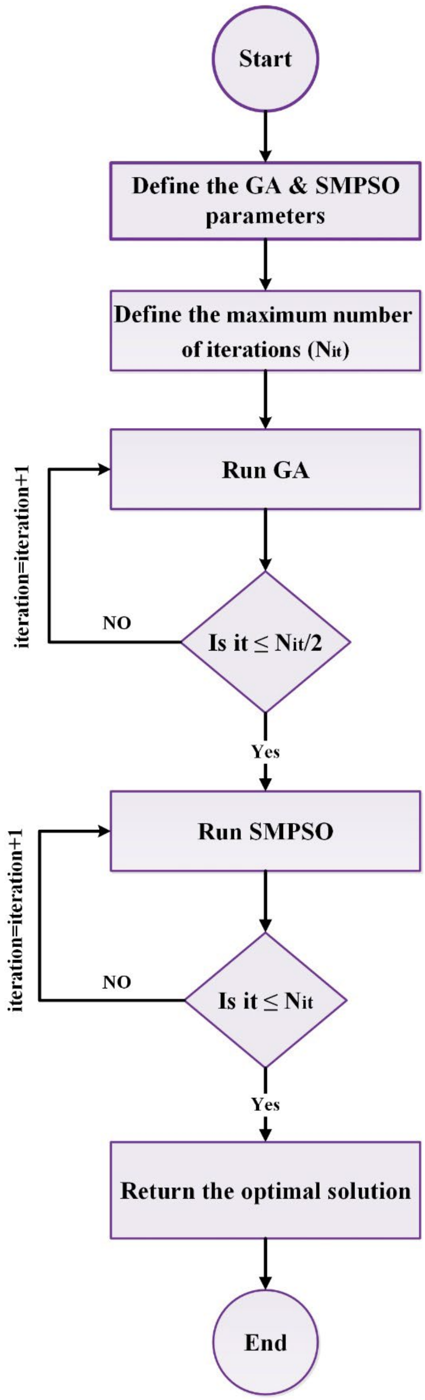

Fig. 1. Flowchart of the SGAPSO algorithm.

for hydraulic computation by EPANET 2.0 and computed the node's pressure, velocity, and head loss gradient pipes. The computed parameters are compared to the standard values as the network constraints. The objective function will be calculated after applying the penalty function if the constraints are not satisfied. This process will be repeated between the simulation and optimization phases until the conditions are satisfied. Fig. 2 shows the applied solution methodology in this paper.

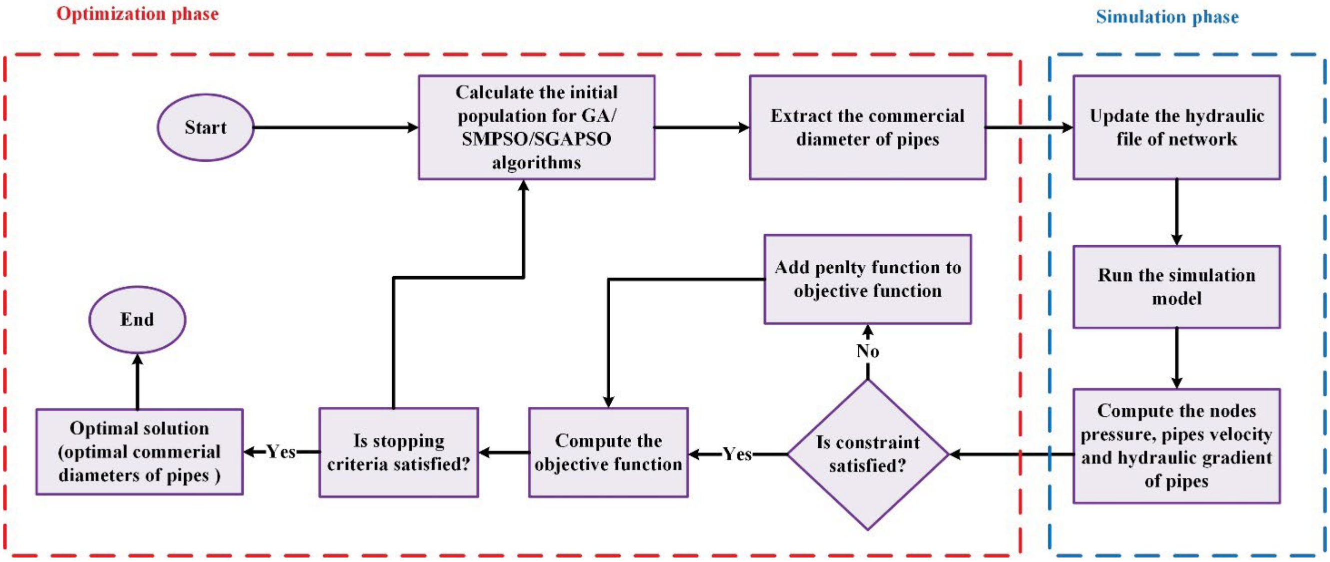

Fig. 2. Solution methodology.

6. Results and discussion

In this section, the performances of GA, SMPSO, and SHGAPSO for optimization of WDN design problems are evaluated by applying them to a real-life WDN in Iran. This network was already designed and the cost of the network was available, and optimized by a consulting private company.

6.1. Jangal network

The WDN of Jangal is skelebrated and includes 37 pipes, 24 nodes, and one reservoir with the head of 962 m (Fig. 3). The aim of the optimal design of this network is the rehabilitation and expansion of the existing WDN. To reach this purpose, some of the existing pipes that are of diameters larger than 100 mm were involved in the analysis of future conditions. Polyethylene pipes with a Hazen–Williams coefficient of 130 have been used to design the network. The details of nodes and pipes of the network are presented in Table 2, and the set of commercially available polyethylene pipe diameters along with the pertinent costs are presented in Table 3. In this article, the minimum and the maximum pressure limit areas were summed to be maintained within 14–60 m, respectively, and the minimum allowed velocity must not be lower than 0.2 m/s [49].

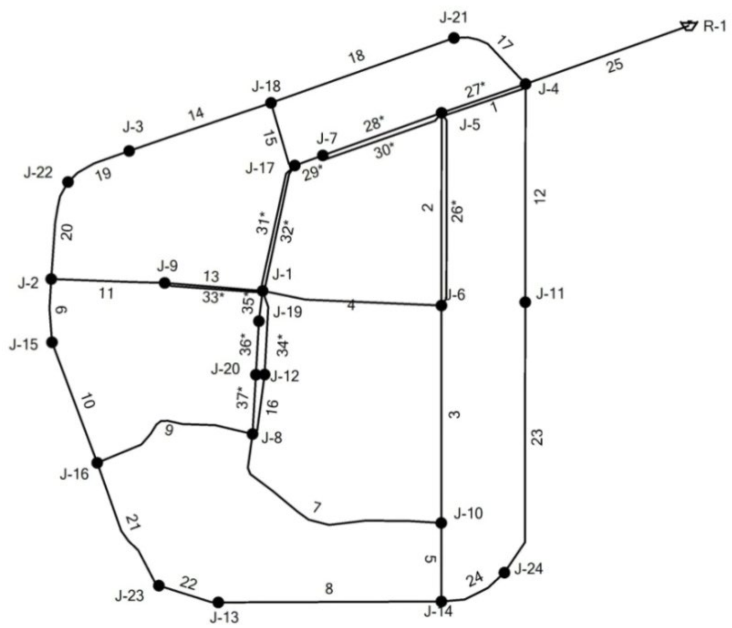

Fig. 3. Layout of Jangal network.

Table 2
Network data for the Jangal network

	Pipe number	1	2	3	4	5	6	7	8	9	10	11	12	
Pipe data	Length (m)	287.73	624.54	705	582.78	254.51	205.44	805.59	723.29	556.56	417.27	367.89	707.14	
	Pipe number	13	14	15	16	17	18	19	20	21	22	23	24	
	Length (m)	320.95	485.55	226.47	201.47	292	628.8	225.25	323.09	451.71	200.86	897.33	232.56	
	Pipe number	25	26*	27*	28*	29*	30*	31*	32*	33*	34*	35*	36*	37*
	Length (m)	9,999.87	634.90	299.62	409.04	96.62	423.98	427.02	422.15	318.52	274.62	99.06	174.04	192.33
	Node number	1	2	3	4	5	6	7	8	9	10	11	12	
Node data	Elevation (m)	901.5	896.5	895.5	903.5	903.5	902.5	901.5	900	900.5	900.5	903.5	902	
	Demand (m^3/h)	21.78	7.81	20.56	7.56	22.64	30.13	13.25	32.58	18.86	32.8	14.29	0	
	Node number	13	14	15	16	17	18	19	20	21	22	23	24	
	Elevation (m)	899	905	898	900.5	900.5	899.5	901.5	902	902	898	900.5	904	
	Demand (m^3/h)	18.79	9.54	7.45	15.8	11.02	16.31	0	0	0	0	0	0	

*These are the existing pipes of the network whose costs are not taken into account.

Fig. 4 demonstrates the convergence rate graph of the optimization algorithms when applied to Jangal network.

In order to avoid the impact of the random nature of the initial population on the convergence, the algorithms were run 10 times and all the results were presented in Table 4. As can be seen, the SHGAPSO algorithm obtained the best value at a cost of 1.034 × 10^9 rials over 10 times run of the GA, SMPSO, and SHGAPSO algorithms.

As observed, not only the rate of convergence is improved in the SHGAPSO, but also it is possible to obtain a solution at a lower cost than those of the other two methods (GA and SMPSO methods). In this study, to eliminate the effect of the random nature of the initial population on the convergence rate, the initial population generated randomly was considered the same for all the three algorithms.

The results obtained for the Jangal network using the three optimization methods are listed in Tables 5 and 6 in comparison with the ones suggested by the consulting engineers' company. As can be seen, the constraints representing nodal pressure limits, velocity, and head loss gradient in pipes are within the permissible range.

Table 7 shows the final costs along with a summary of the results obtained for the Jangal network when it was

Table 3
Pipe sizes and costs for Jangal network

Pipe number	Diameter (mm)	Cost (Rial/m)	Pipe number	Diameter (mm)	Cost (Rial/m)
1	76.6	49,560	6	191.8	305,200
2	93.8	73,360	7	213.2	375,200
3	106.6	94,360	8	238.8	470,400
4	136.4	154,000	9	268.6	593,600
5	170.6	239,680	10	302.8	753,200

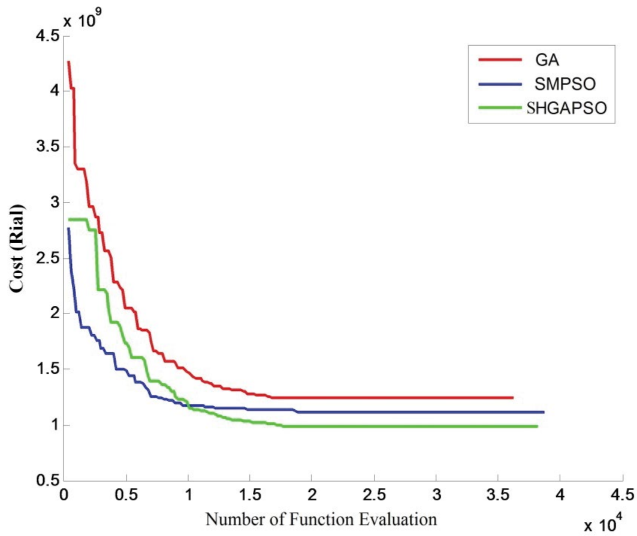

Fig. 4. Convergence of GA, SMPSO, and SHGAPSO algorithms in Jangal network optimization.

Table 4
Result of running algorithms 10 times

Run number	Methods			
	Consulting company (10^6 rials)	GA (10^6 rials)	SMPSO (10^6 rials)	SHGAPSO (10^6 rials)
1	1.403	1.169	1.144	1.112
2		1.305	1.204	1.201
3		1.178	1.213	1.156
4		1.170	1.161	1.068
5		1.403	1.329	1.321
6		1.245	1.247	1.221
7		1.167	1.102	1.034
8		1.185	1.119	1.114
9		1.190	1.170	1.155
10		1.180	1.122	1.034
Best	1.403	1.167	1.102	1.034
Worst	1.403	1.403	1.329	1.321
Average	1.403	1.219	1.181	1.142
Standard deviation	0.000	0.074	0.066	0.085

optimally designed by the four different methods. Since the pipeline (pipe 25) is quite long, all four methods have assigned the largest available diameter to it. The cost of this pipe has been disregarded at the final costs, so only those of the designed pipes (pipes 1–24) have been taken into account. As can be seen, SHGAPSO outperforms the other two algorithms, giving a design cost by 26% lower than the one suggested by the consulting engineers, while GA and SMPSO have presented optimal solutions with 16% and 21% cost reduction, respectively. Furthermore, in GA, SMPSO, and SHGAPSO, the minimum velocity constraint of the pipes, which is 0.2 m/s, is satisfied unlike that of the consulting engineers' method in which it is 0.13 m/s. All the other constraints have been met by all four methods.

To show the difference between network optimal design by an applied method in this study and the earlier methods, the design of the Jangal network was optimized by only using SHGAPSO algorithm and the constraint was considered as the maximum velocity constraint equal to 2 m/s [49] without considering maximum head loss gradient constraint. Table 8 presents results of optimal design using SHGAPSO algorithm in two conditions: (I) maximum head loss gradient was defined as the constraint and (II) maximum velocity equal to 2 m/s was considered as the constraint.

Fig. 5–7 show pressure changes in nodes, velocity, and head loss gradient in pipes in both conditions I and II. Based on Table 7, the standard deviation of the pressure nodes in the design condition II with a value of 4.92 m is greater than that of condition I. It is also evident in Fig. 5 because the pressure nodes variations in design condition I are less than condition II. Furthermore, the pressure uniformity and surplus pressure in the nodes increase when the network is designed with condition I. In this case, the hydraulic reliability of the network increases to compensate for the deficiency pressure in the state of pipes and pumps failure [50].

Similarly, the standard deviation, velocity variations, and head loss gradients in pipes in design condition II are much higher than in design condition I. Fig. 6 demonstrates that the maximum velocity in design condition II increases to 1.72 m/s, while in design condition I the velocity changes within the range of 0.21–1.07 m/s. Fig. 7 demonstrates that the head loss gradient in design condition II has very high variations and higher values in comparison to design condition I, which results in a large loss of water energy in the pipes of network and flow turbulence.

It can be concluded that in the proposed optimal design method presented in this paper and with using the maximum head loss gradient constraint, even though the network design cost increased by 27.74% economically compared to the design condition I and hydraulics parameters of the network were designed at optimum values, reliability increased, and energy loss decreased.

6.2. Sensitivity analysis

The most important step before starting the optimization process is to find the best value for the algorithm parameters. To reach this purpose, the parameters of SMPSO and GA algorithms were changed in their standard range and their sensitivity was calculated. Due to the importance of the initial population size for the start of the algorithm, first, this parameter was examined. At the outset, different initial populations were introduced to the SMPSO and GA algorithms and the best one was selected for the Jangal network. As can be seen from Fig. 8 population size 50, 100, 150, 200, 250, and 300 were examined. Least cost was obtained by considering the population size equal to 200 for both algorithms equal to 1.329×10^9 and 1.403×10^9 Rials, respectively. While determining population size for SMPSO algorithm the values of $w = 0.9$, $w_{damp} = 1$, and $c_1 = c_2 = 2$ and for GA algorithm $P_c = 0.8$ (crossover probability), $P_m = 0.5$ (mutation probability), and $m_u = 0.01$ (mutation rate) was selected by default.

By considering the population size of 200, w value in its standard range increased from 0.4 to 0.9 and its behavior was investigated. The least cost of the network was obtained (1.228×10^9 Rials) by $w = 0.4$ (Fig. 9). By iterative runs of the algorithm, the appropriate interval for w_{damp} was suggested (0.99–1). Finally, after sensitivity analysis in this interval, the optimum solution was obtained at $w_{damp} = 0.998$ equal to 1.128×10^9 Rials (Fig. 10). The tests were performed on the values of c_1 and c_2 within their permissible range [2–4] and as seen in Fig. 11, c_1 and c_2 are very sensitive parameters and it is time-consuming to determine their exact values. The minimum cost was obtained from $c_1 = c_2 = 2.05$ and equal to 1.102×10^9 Rials after examining the simultaneous changes of these two parameters.

Based on previous research on the optimal design of water and wastewater networks using GA, the Roulette Wheel method is better than other random and tournament selection methods. Also, the uniform crossover operator performs better than single-point and two-point crossover [10,51]. Thus in this paper, the Roulette Wheel method and uniform crossover operator were applied. To examine the

Table 5
Comparison of the diameter, velocity, and headloss gradient in pipes using GA, SMPSO, SHGAPSO, and consulting company methods

Pipe number	Diameter (mm)				Velocity (m/s)				Headloss Gradient (m/km)			
	Consulting company	GA	SMPSO	SHGAPSO	Consulting company	GA	SMPSO	SHGAPSO	Consulting company	GA	SMPSO	SHGAPSO
1	268.6	170.6	170.6	191.8	0.8	0.98	1.08	1.07	2.71	6.57	7.79	6.75
2	136.4	76.6	76.6	93.8	0.8	0.47	0.58	0.71	5.74	4.17	6.19	7.04
3	213.2	93.8	136.4	170.6	0.47	0.71	0.73	0.67	1.27	7.08	4.77	3.15
4	136.4	106.6	106.6	106.6	0.51	0.73	0.61	0.52	2.50	6.33	4.64	3.35
5	106.6	136.4	76.6	93.8	0.49	0.42	0.20	0.65	3.03	1.76	0.82	6.04
6	93.8	136.4	136.4	106.6	0.59	0.45	0.45	0.57	5.12	1.98	2.04	4.05
7	93.8	93.8	93.8	76.6	0.49	0.29	0.35	0.37	3.48	1.30	1.90	2.62
8	93.8	76.6	76.6	93.8	0.63	0.67	0.63	0.62	5.56	7.93	6.98	5.37
9	93.8	76.6	76.6	76.6	0.47	0.45	0.47	0.51	3.24	3.81	4.15	4.88
10	93.8	106.6	106.6	93.8	0.29	0.50	0.51	0.43	1.37	3.16	3.30	2.80
11	93.8	106.6	106.6	76.6	0.40	0.50	0.49	0.41	2.38	3.17	3.09	3.21
12	106.6	170.6	136.4	106.6	0.74	0.69	0.71	0.72	6.58	3.37	4.58	6.15
13	93.8	106.6	106.6	76.6	0.58	0.63	0.63	0.57	4.80	4.93	4.87	5.97
14	136.4	136.4	136.4	136.4	0.63	0.68	0.69	0.76	3.69	4.23	4.36	5.14
15	93.8	76.6	76.6	76.6	0.47	0.44	0.40	0.55	3.35	3.75	3.15	5.56
16	93.8	93.8	93.8	106.6	0.57	0.58	0.56	0.51	4.72	4.95	4.61	3.36
17	136.4	136.4	136.4	136.4	0.72	0.85	0.87	0.89	4.74	6.48	6.82	7.08
18	136.4	136.4	136.4	136.4	0.72	0.85	0.87	0.89	4.67	6.38	6.71	6.97
19	93.8	93.8	93.8	106.6	0.51	0.61	0.64	0.6	3.89	5.44	5.83	4.48
20	93.8	93.8	93.8	106.6	0.51	0.61	0.64	0.6	3.86	5.40	5.79	4.44
21	93.8	76.6	93.8	76.6	0.13	0.46	0.34	0.21	0.28	4.02	1.78	0.91
22	93.8	93.8	106.6	76.6	0.13	0.31	0.26	0.21	0.29	1.52	0.97	0.92
23	106.6	136.4	106.6	76.6	0.30	0.81	0.72	0.53	1.21	5.85	6.22	5.08
24	106.6	136.4	136.4	76.6	0.30	0.81	0.44	0.53	1.23	6.01	1.92	5.14
25	341.2	341.2	341.2	341.2	0.91	0.91	0.91	0.91	2.46	2.47	2.47	2.47
26*	170.6	170.6	170.6	170.6	0.92	0.5	0.95	1.02	5.64	4.10	6.09	6.92
27*	200	200	200	200	0.61	1.08	1.07	0.99	2.60	6.31	7.48	6.48
28*	106.6	106.6	106.6	106.6	0.65	0.59	0.71	0.71	5.23	5.91	6.08	6.07
29*	170.6	170.6	170.6	170.6	0.95	0.84	1.05	1.04	6.68	7.71	7.96	7.95
30*	170.6	170.6	170.6	170.6	0.86	0.77	0.93	0.93	5.04	5.70	5.86	5.86
31*	136.4	136.4	136.4	136.4	0.77	0.94	0.94	0.91	5.29	7.33	7.77	7.26
32*	93.8	93.8	93.8	93.8	0.61	0.75	0.75	0.73	5.35	7.41	7.86	7.34
33*	93.8	93.8	93.8	93.8	0.58	0.6	0.58	0.65	4.83	4.96	4.91	6.02
34*	93.8	93.8	93.8	93.8	0.57	0.57	0.56	0.66	4.69	4.92	4.57	6.21
35*	136.4	136.4	136.4	136.4	0.34	0.34	0.34	0.35	1.25	1.31	1.22	1.33
36*	106.6	106.6	106.6	106.6	0.56	0.56	0.55	0.58	3.99	4.18	3.89	4.24
37*	93.8	93.8	93.8	93.8	0.72	0.73	0.71	0.75	7.39	7.75	7.21	7.86

*These are the existing pipes of the network whose costs are not taken into account.

Table 6
Nodal pressures of Jangal network obtained by GA, SMPSO, SHGAPSO, and the consulting company

SHGAPSO	SMPSO	GA	Consulting company	Node Number	SHGAPSO	SMPSO	GA	Consulting company	Node Number	SHGAPSO	SMPSO	GA	Consulting company	Node Number
31.6	30.53	31.38	33.2	17	26.6	23.97	23.51	29.4	9	27.5	26.96	27.59	29.9	1
31.3	25.20	25.74	33.4	18	26.2	23.02	23.24	29.5	10	29.4	29.25	29.84	32.5	2
27.4	26.84	27.46	29.8	19	29.4	27.34	27.94	29.1	11	32.8	33.43	30.80	35.6	3
26.1	25.66	26.23	28.6	20	25.3	23.47	24.13	28.2	12	33.8	33.76	33.76	33.8	4
33.2	33.27	33.37	33.9	21	24.3	31.27	31.71	28.2	13	31.8	31.52	31.87	33	5
29.3	29.62	30.08	32.3	22	22.2	31.55	31.86	26.2	14	28.4	28.66	30.27	30.4	6
23	22.66	22.31	26.8	23	27.1	31.04	31.45	30	15	31.3	26.27	26.74	32.8	7
24.4	24.46	25.64	27.5	24	23.4	26.39	27.01	26.9	16	26.6	25.31	25.29	29.2	8

Table 7
Summary of the results obtained using GA, SMPSO, SHGAPSO, and consulting company method

Method	Consulting company	GA	SMPSO	SHGAPSO
Cost (Rial × 10^9)	1.403	1.167	1.102	1.034
Minimum velocity (m/s)	0.13	0.28	0.20	0.21
Minimum pressure (m)	26.2	22.31	22.66	22.20
Maximum pressure (m)	35.6	33.80	33.76	33.80
Maximum headloss gradient (m/km)	7.39	7.93	7.96	7.94

Table 8
Comparison of results in two conditions I and II using SHGAPSO algorithm

	Node		Pipe				Cost (Rial)	
	Pressure (m)		Velocity (m/s)		Headloss gradient (m/km)			
	I	II	I	II	I	II	I	II
Minimum	22.20	14.06	0.21	0.33	0.91	2.10	1.034×10^9	7.471×10^8
Maximum	33.80	33.76	1.07	1.72	7.95	18.58		
Average	28.02	21.81	0.66	0.79	5.04	8.30		
Standard deviation	3.32	4.92	0.22	0.31	1.91	4.68		

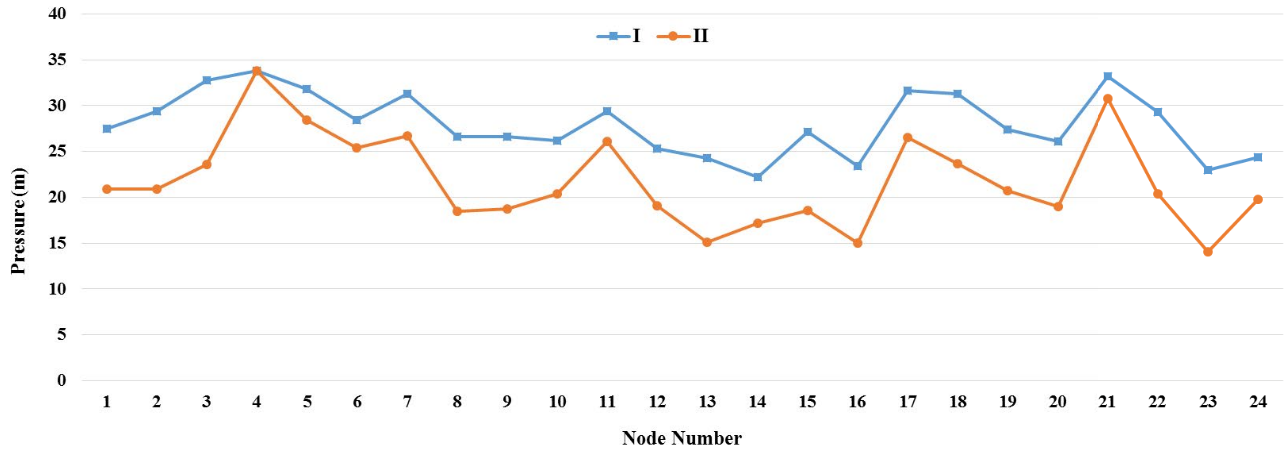

Fig. 5. Nodes pressure variations in network optimal design for condition I and II.

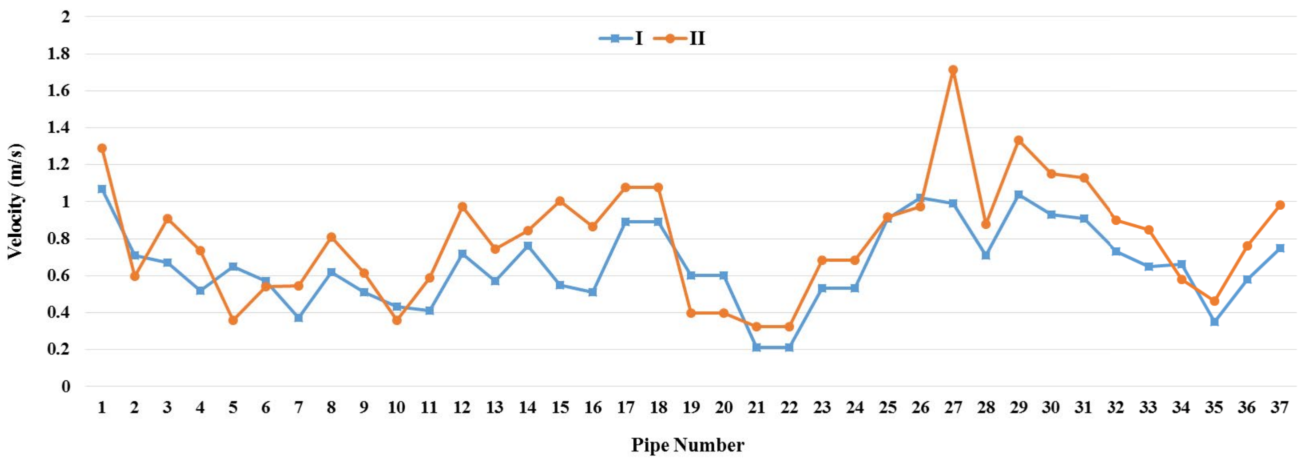

Fig 6. Pipes Velocity variations in network optimal design for condition I and II.

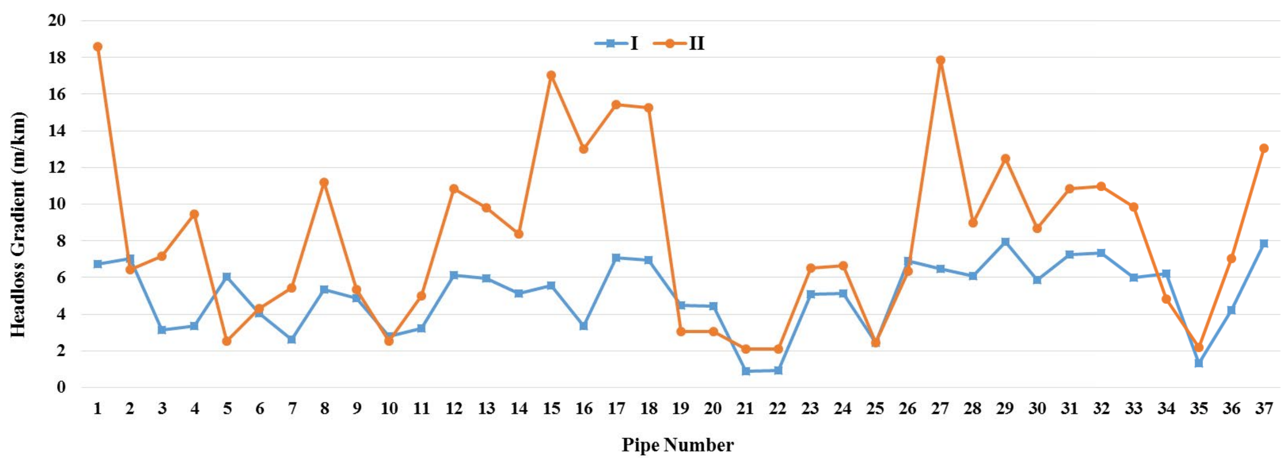

Fig 7. Pipes headloss gradient variations in network optimal design for condition I and II.

sensitivity of P_c and P_m parameters, their values were changed from (0.6–1) to (0.1–1), respectively, and their best values for Jangal network were obtained $P_c = 0.8$ (cost = 1.293×10^9 Rials) and $P_m = 0.3$ (cost = 1.182×10^9 Rials) (Figs. 12 and 13). The mutation is one of the most important GA operators and in this paper, its values increased from 0 to 0.05 (Fig. 14). The network cost was reduced to 1.167×10^9 by $m_u = 0.01$ but by increasing the mutation rate to 0.04, the cost gradually increased. In SHGAPSO, the algorithm parameters are the same as those of the sub-algorithms.

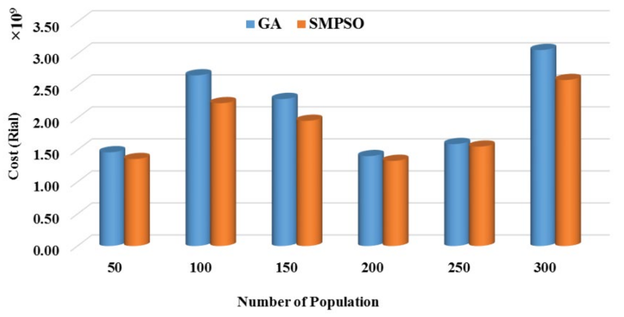

Fig. 8. Changes of population size of SMPSO and GA algorithms for the Jangal network.

7. Conclusions

In this research, GA, a modified version of PSO, and a novel hybrid optimization algorithm referred to as SHGAPSO, were utilized to optimize the pipe sizes of WDNs. The performances of these methods were then evaluated by applying them to a real-life WDN in Iran, Jangal city. Additionally, an engineering idea was taken into account which is a practical constraint on the head loss gradient in pipes. The proposed constraint replaces the maximum velocity limit. The results demonstrated that SHGAPSO remarkably outperforms the other two algorithms as it could find an optimal design with a cost lower than that of the configuration suggested by the consulting company. This is while the cost reductions obtained by GA and SMPSO were 16% and 21%, respectively. Moreover, in GA, SMPSO, and SHGAPSO methods the constraint on minimum velocity in the pipes, which was 0.2 m/s, was

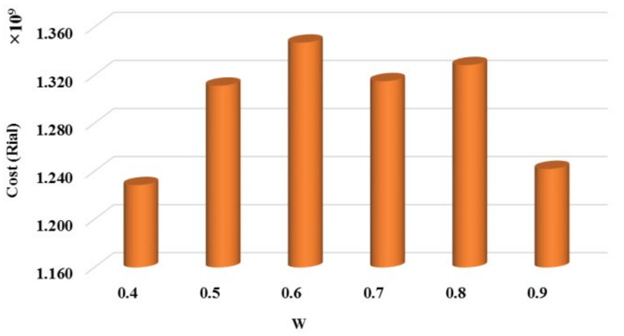

Fig. 9. Changes of w for Jangal network.

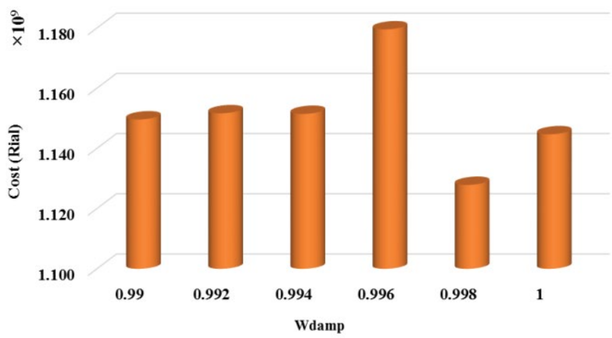

Fig. 10. Changes of w_{damp} for Jangal network.

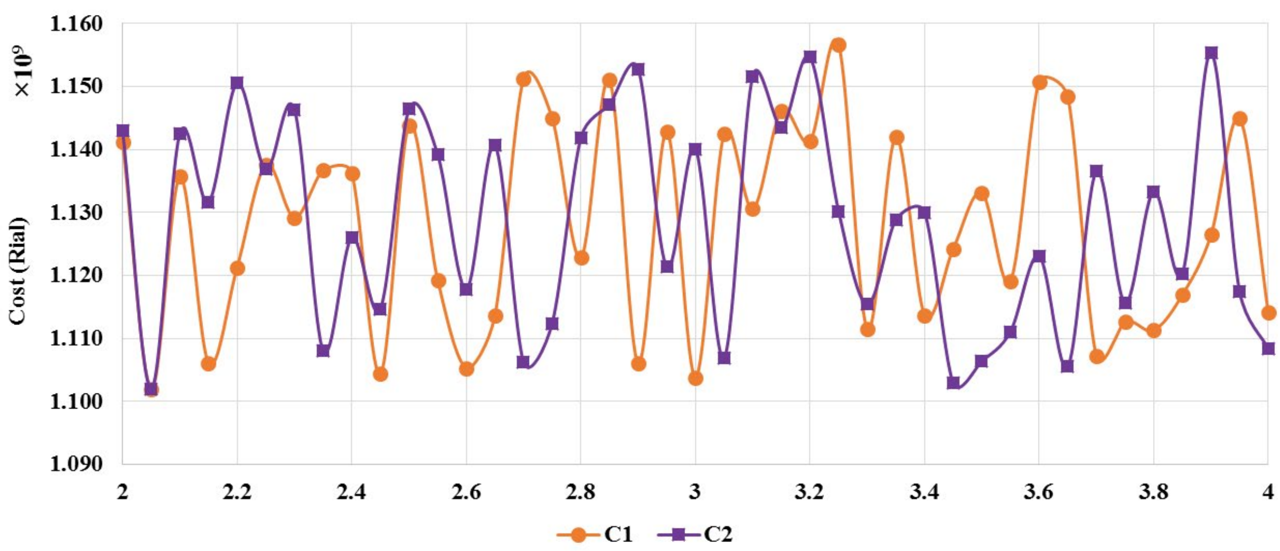

Fig. 11. Changes of c_1 and c_2 for Jangal network.

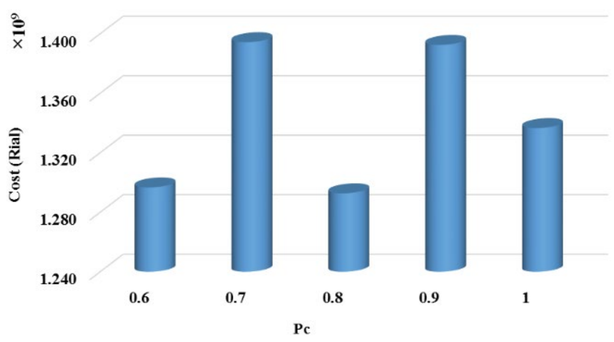

Fig. 12. Changes of P_c for Jangal network.

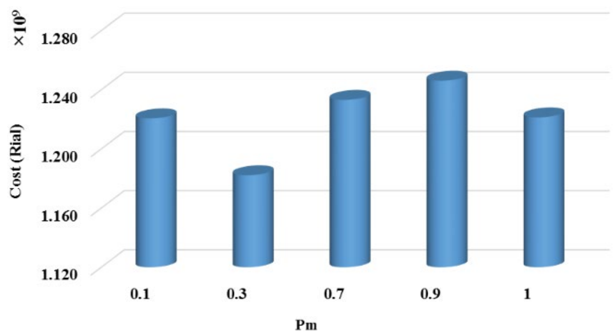

Fig. 13. Changes of P_m for Jangal network.

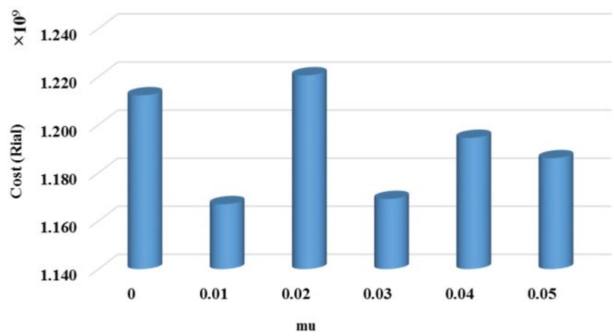

Fig. 14. Changes of m_u for Jangal network.

met unlike the one obtained using the method employed by the consulting company, in which the minimum velocity is 0.13 m/s. The convergence rate is considerably better in case the SMPSO algorithm is used. It was observed that widely explores the search space, leading to a lower convergence rate than that of SMPSO. In short, it can be concluded that the SHGAPSO algorithm has kind of removed the restrictions of GA and SMPSO in a way that the resulting hybrid algorithm performs quite better when finding the least-cost design of WDNs. Furthermore, to show the performance of the introduced constraint (maximum head loss gradient per 1,000 m) in this study, the optimal design of the studied network was evaluated in both cases with and without considering this constraint. The results showed that the application of maximum head loss gradient leads to not only uniformity and excess pressure in the nodes to the minimum permissible pressure and an increase in network hydraulic reliability but also uniformity and reduction of velocity and head loss gradient in pipes which consequently results in network energy loss reduction.

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