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Optimal design of water distribution networks using simple modified particle swarm optimization approach

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ABSTRACT

Water distribution networks design belongs to a class of large combinatorial nonlinear optimization problems, involving complex implicit constraints, such as conservation of mass and energy equations, which are commonly satisfied by using hydraulic simulation solvers. Recently, many researchers have shifted the focus of traditional optimization methods to the use of metaheuristic approaches for handling this complexity. Particle swarm optimization (PSO) is one of the evolutionary algorithms which was developed for optimization problems with continuous variables. Also it has been adapted successfully in other problems contexts with discrete variables. In this research, a simple modified particle swarm optimization (SMPSO) was applied to minimize water distribution networks cost. The SMPSO was used as novel factor to decrease inertia weight linearly with time for each iteration to facilitate the balance of global and local researches. The SMPSO algorithm was linked to a hydraulic simulator, EPANET 2.0. This approach was applied to three benchmark in water distribution network optimization problems. The results indicate that a significant improvement in performance of PSO could be achieved by decreasing inertia weight over the iterations.

Keywords: SMPSO; Inertia weight; EPANET 2.0; Water distribution networks

1. Introduction

The efficiency is one of the main elements in designing new water distribution networks (WDNs). The optimal design of WDNs has been studied comprehensively over the past few decades due to its computational and engineering complexity. Most of these studies focused on the least-cost optimization. However, it is necessary to investigate the reliability of network design to ensure the sufficient head. Moreover the existence nonlinear relation between flow, head-loss, and discrete variables such as pipe diameter in optimal design of WDNs is a highly challenging problem.

In the last decade, several new nontraditional optimization methods for such non-deterministic polynomial-time (NP)-hard problems, which contain nonlinear, constrained, non-smooth, non-convex, and multimodal functions, have been explored [1]. At first, most of the optimization techniques made some initial solution, then using deterministic search methods, until no more reduction in cost took place. Therefore, the final solution depended on the initial solution.

Yates et al. [2] stated that either explicit enumeration or an implicit enumeration technique such as dynamic programming could guarantee the optimal solution to NP-hard WDN design problem. For example, in a WDN with 20 number of pipes and 10 commercially available pipe sizes, the total number of solutions is 10^{20}, giving a very wide search space. Therefore, the complete enumeration method for real

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size WDN problems becomes stubborn. Gessler [3] proposed a partial enumeration technique in which certain inferior solutions were rejected from being evaluated by the hydraulic simulation model. In addition, partial enumeration techniques are difficult to use for the optimal design in large size realistic WDNs.

Many studies in literature have focused on minimizing the costs of the objective function in optimization of WDNs such as linear programming, nonlinear programming (NLP), enumeration techniques, heuristic methods, and evolutionary techniques. Alperovits and Shamir [4] applied the linear programming gradient method that is a linearization model. Many researchers [5–7] have developed approaches for obtaining the global optimum and dominated by linearization technique limitations. Moreover, many researchers [8–13] have applied the NLP optimization approach to pipe network problems due to the nonlinear nature of these problems. The NLP techniques do not guarantee the identification of global optimal solution because they depend on the initial solution and practice of discrete variables, such as commercial pipe diameters, reduces the quality of optimal solution [14].

Additionally, the research applied the stochastic optimization models such as genetic algorithms (GAs), simulated annealing (SA), harmony search optimization (HS), shuffled frog leaping algorithm (SFLA), ant colony optimization (ACO), differential evolution (DE), and shuffled complex evolution (SCE) in optimal design of WDNs. The search strategy in most of these models is based on the objective function values to move to a better solution in successive iterations and efficient in handling discrete variables. Some researchers [15–24] applied GAs for solving network design problems. Simulated annealing used by Loganathan et al. [25] and Cunha and Sousa [26]. Geem et al. [27], Geem [28], Yazdi [29], and Eusuff and Lansey [30] developed the HS method and the SFLA. Maier et al. [31] used the ACO approach and outperformed GAs both in terms of computational efficiency and their ability to find near global optimal solutions. Shie-Yui Liong [32] and Vasan and Simonovic [14] applied the SCE and DE approach, respectively.

Particle swarm optimization (PSO) is one of the evolutionary algorithms, which has proven its possibility and performance in solving various optimization problems [33–37]. The PSO algorithm was developed by Kennedy and Eberhart [38] and inspired by the social behavior of a group of migrating birds trying to reach an unknown destination. This algorithm with certain modifications was used in this research to find solutions for the optimal design in water supply networks.

In this study, a simple modified PSO (SMPSO) is introduced initially. This model uses a new constant factor to decrease inertia weight linearly using time for each iteration. This strategy can significantly facilitate the balance of global and local searches. In the following steps, the performance of this algorithm is evaluated for two standard benchmark networks, and the results are compared with the previous studies. Also, the sensitive analysis was performed for determining the best parameter values of SMPSO algorithm on the network. The optimization problems addressed herein linked with hydraulic simulator of EPANET 2.0 [39]. The goal is to minimize the cost, with pipe diameter as decision variables.

2. Optimal design of a water distribution network

The optimal design of a WDN is often noticed as a least-cost optimization problem. The decision variables are the diameters of each pipe in WDN. The optimal solution is obtained by minimizing the total cost. For a given layout, the source head, elevation and demand values for nodes, pipe lengths and pipe roughness are known in advance. The objective is to find a combination of different sizes of pipe that can satisfy the nodal head constraints at the lowest cost. In order to facilitate the comparison of results obtained by other authors, the following objective function was used to minimize the cost for a WDN by Eq. (1):

$$F_{\text{obj}} = \sum\nolimits_{i=1}^{n} C_{D_i} L_i \tag{1}$$

where D_i, L_i, and C_{Di} are the diameter, the length and the unit cost of the i-th pipe, respectively, and n is the total number of pipes in the network. Typically, the constraints of WDNs optimization include: flow continuity at each node, energy conservation in each primary loop, and the minimum allowable head requirement at each node. These constraints can be mathematically expressed as:

$$q_j^{\text{in}} - q_j^{\text{out}} - q_j = 0 \qquad j = 1,2,\ldots,d_j; \tag{2}$$

$$\left(\sum\nolimits_{i=1}^{\text{npl}} \text{HL}_i\right)_L = 0 \qquad L = 1,2,\ldots,\text{nL}; \tag{3}$$

$$H_j \geq H_j^{\min} \qquad j = 1,2,\ldots,\text{nd}; \tag{4}$$

$$D_{\min} \leq D \leq D_{\max} \tag{5}$$

where q_j^{in} is the flow entering at node j, q_j^{out} is the flow leaving at node j towards the downstream nodes, q_j is the demand at node j, HL_i is the head loss in pipe i, np_l is the number of pipes in a loop, nL is the number of loops in the WDN, H_j is the hydraulic head available at node j, $H_j^{\min}$ is the minimum hydraulic head required at node j, d_j is the number of demand nodes, and in this context, $D_{\min}$ and $D_{\max}$ are the minimum and maximum allowable pipe sizes, respectively. The loop refers to the closed circuit formed by the pipes. Eq. (2) is referred to as the nodal mass balance equation; Eq. (3) is referred to as the loop energy balance equation; Eq. (4) is the minimum hydraulic head requirement constraint and Eq. (5) is the constraint for the pipe diameters.

The head loss in each pipe is the head difference between connected nodes, and can be computed using the Hazen–Williams equation:

$$\text{HL} = \omega \frac{L_i}{C_i^{\alpha} D_i^{\beta}} q_i^{\alpha} \tag{6}$$

where ω is a numerical conversion constant (dependent on units); C_i is roughness coefficient of pipe i (dependent on material); α and β are regression coefficients.

Researchers have used different values for the numerical conversion constant ω and regression coefficients α and β. The higher constant ω, the greater the head loss is and vice versa. Thus, an optimal solution with higher value of ω will be costlier than solution with lower value of ω [28]. Savic and Walters [18] reported the smallest and largest value of ω used in the literature as 10.5088 (α = 1.85, β = 4.87) and 10.9031 (α = 1.852, β = 4.87). Cunha and Sousa [26] and Geem et al. [27] used ω = 10.5088 (α = 1.85, β = 4.87). Eusuff and Lansey [30] and Shie-Yui Liong [32] coupled their algorithms with EPANET 2.0 in which ω = 10.667 (α = 1.852, β = 4.871).

To solve the problem mentioned above, the constrained model is converted into an unconstrained one by adding the amount of constraint violations to the objective function as penalties. Although the conservation of mass and energy constraints are satisfied externally via EPANET 2.0 [32], the pressure constraint is required to be considered in the penalty costs. Thus, the total cost of the network is considered as the sum of the network cost and a penalty cost is defined as Eq. (7):

$$F_{\text{obj}} = \sum_{i=1}^{n} C_{D_i} L_i + \text{PF} \tag{7}$$

The penalty function PF only applies when the pressure in any node is less than a predetermined minimal value. For nodes with pressure larger than this minimal value, the associated individual penalties are vanished, and 1 is used as the usual Heaviside step function $\vartheta_{\text{Heaviside}}$ in the explicit expression for PF as Eq. (8):

$$\text{PF} = \sum_{j=1}^{\text{nd}} \vartheta_{\text{Heaviside}} \left(H_j^{\min} - H_j \right) . a . \left(H_j^{\min} - H_j \right) \tag{8}$$

where a is the penalty multiplier that is defined by user and in this study is assumed to be 9 × 10^9.

3. Hydraulic simulator: EPANET 2.0

EPANET 2.0 is a robust model which is used by a large community of users in the world in order to run the hydraulic simulations of the WDNs [39]. It combines all the main infrastructures of supplying systems, such as gravity and pump systems, valves (e.g., relief, pressure reducing, regulating, control and isolation valves), reservoirs (of fixed or variable level), by which it is possible to make operating conditions. EPANET 2.0 calculates flow in each pipe, pressure in each node, water level in each reservoir and concentration of chemicals during the simulation period. It considers the balance conditions, for a set of equations, using the method of gradient and runs static and quasi-steady simulations of the hydraulic and water quality situation of pipe network [27].

4. Simple modified particle swarm optimization algorithm

PSO is a promising new optimization technique developed by Kennedy and Eberhart [38] which models a set of potential solutions as a swarm of particles moving about in a virtual search space. The method was inspired by the movement and interaction of flocking birds with their neighbors in the group. A swarm of P particles optimizes in n-dimension search space. Each particle i has position $X_i^t = (x_{i1}, x_{i2}, ..., x_{is})$ and velocity $V_i^t = (v_{i1}, v_{i2}, ..., v_{is})$ at iteration t. Each particle keeps tracking of its position vector pbest, which has achieved the best fitness function so far. The position vector gbest, which is the best value of fitness function, obtained by any particle so far that is also remembered. The values of the fitness function for these are stored. The PSO concept consists of changing the velocity of each particle toward its pbest and gbest. Once the velocities are determined, then position vectors of the particles will be updated. At these updated positions, the fitness function is recalculated and the position vectors pbest and gbest are updated. This process continues until the given iterations are over. The following equations were used, which iteratively modify the particle velocities V_{ij}^t and positions X_{ij}^t at iteration number t: [37,40]

$$V_{ij}^{t+1} = wV_{ij}^t + c_1 r_1^t \left(\text{pbest}(ij) - X_{ij}^t \right) + c_2 r_2^t \left(\text{gbest}(\text{j}) - X_{ij}^t \right) \tag{9}$$

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

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 [0,1]. The position vector gbest (global best position) and pbest (particle best position) are modified during the iteration. Proper fine-tuning of the parameters c_1 and c_2 in Eq. (9) may result in faster convergence of the algorithm, and alleviation of the problem of local minima. To control the changes in velocity, Clerc [41] introduced the constriction factor into the standard PSO algorithm to ensure the convergence of the search. The role of inertial weight w in Eq. (9) is controlling the impact of previous velocities on the current one. A large inertial weight facilitates global exploration (searching new areas), while a small weight tends to facilitate local exploration. Hence, selection of a suitable value for the inertial weight w usually helps in reduction of the number of iterations that required to locate the optimum solution [42]. Shi and Eberhart [43], Shi and Eberhart [44] suggested that the allowable of w changes between 0.4 and 0.9, in standard PSO algorithm.

In this research, a SMPSO is present by using a reduction factor, w_{damp}, to adjust the convergence speed of an algorithm to find the optimal solution. It is important to determine the appropriate value of w_{damp}, as it reduces w following a linear form in each iteration:

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

To manage any changes in the particle velocities, the relevant upper and lower limits were defined as follows:

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

The standard PSO algorithm is applicable to continuous problems and cannot use for discrete problems. Various approaches were put forward to tackle discrete problems with PSO [34,35]. Essentially, this algorithm only takes integer parts of flying velocity vector components into account. Following the new velocity V_{ij}^{t+1}, that is an integer, the new position vector components also will be integer (Eq. (13)). As a result, the initial position vectors are generated with integer values.

$$V_{ij}^{i+1} = \text{round}\left(wV_{ij}^{t} + c_1 r_1^t \left(\text{pbest}(ij) - X_{ij}^t\right) + c_2 r_2^t \left(\text{gbest}(j) - X_{ij}^t\right)\right) \tag{13}$$

For discrete variables, round() is a function that takes the integer part of its argument. The particle velocity is computed by Eq. (13) and follows exactly the limits which are established by Eq. (12). V_{max} is calculated by Eq. (14):

$$V_{max} = 0.5.\left(X_{max} - X_{min}\right) \tag{14}$$

where X_{max} and X_{min} are maximum and minimum diameters that can be considered for each network.

5. Testing the benchmark problems

The performance of developed SMPSO-based model for optimization of WDN design problem is evaluated through three well-known benchmark case studies: the two-loop network, the Hanoi network, and the Kadu network. For each case study, a preliminary sensitivity analysis was performed to determine the effective parameter values of the SMPSO algorithm on the basis of the range that was suggested by Clerc and Kennedy [45].

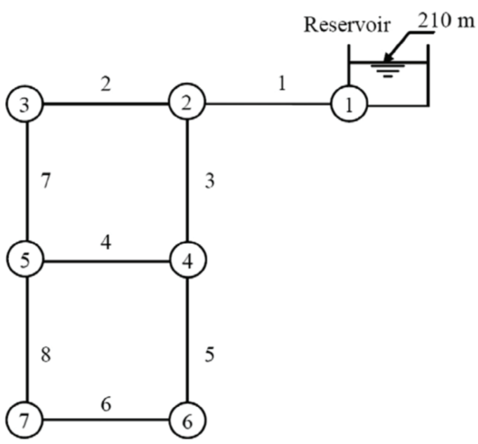

Fig. 1. Layout of the two-loop network.

Table 1
Node demands and elevations for two-loop network

Node number	Elevation (m)	Demand (m^3/h)
2	180	100
3	190	100
4	185	120
5	180	270
6	195	330
7	190	200
Reservoir 1	210	–1,120

5.1. Two-loop network

The two-loop network, which is shown in Fig. 1, was originally presented by Alperovits and Shamir [4]. The network has seven nodes and eight pipes with two loops and is fed by gravity from a reservoir with a 210 m fixed head. Nodal demands and elevations are given in Table 1. The pipes are all 1,000 m length with the assumed Hazen–Williams coefficient of 130. The required minimum head of other nodes is 30 m above ground level. There are 14 commercial diameters for selection and costs for each pipe size are given in Table 2. Thus, the problem search space consists of 14^8 different network designs, which made this illustrative example difficult to solve [18].

The results of this study were compared with the previous researches, which solved this problem by different evolutionary algorithms such as GA, SA, SFLA, HS, and SS (Table 3). According to Table 3, the cost obtained due to the optimization with PSO algorithm is $419,000, which is the minimum cost reported for this network so far and obtained after 3,100 times of number of function evaluation (NFE) (Fig. 2), whereas other methods reached this cost after at least 3,215 times of NFE. The constant of Hazen–Williams equation (ω, Eq. (6)) was considered 10.667, 10.5088, 10.5088, and 10.55879 for PSO, GA, SA, and HS algorithms, respectively. The increase in ω coefficient will increase the head loss of the pipes, so, larger pipe diameters should be selected.

Table 2
Pipe sizes and costs for two-loop network

Pipe number	Diameter (mm)	Cost ($/m)
1	25.4	2
2	50.8	5
3	76.2	8
4	101.6	11
5	152.4	16
6	203.2	23
7	254.0	32
8	304.8	50
9	355.6	60
10	406.4	90
11	457.2	130
12	508.0	170
13	558.8	300
14	609.6	550

Table 3
Results for design of two-loop network by various researchers

Model	Cost ($)	NFE	ω
GA [18]	419,000	250,000	10.5088
SA [26]	419,000	25,000	10.5088
SFLA [30]	419,000	11,323	10.667
HS [28]	419,000	5,000	10.5879
SS [46]	419,000	3,215	10.667
SMPSO (This work)	419,000	3,100	10.667

The obtained diameters of pipes and pressure of nodes for this network are shown in Table 4.

The most important step in starting the optimization is determining the best values for the algorithm parameters. For this purpose, in the two-loop network, SMPSO parameters change within their standard range and their sensitivity is investigated.

At the first step, the initial population sizes of 20, 60, 100, 140, and 180 for the two-loop network was introduced to SMPSO algorithm. The lowest cost of optimization (equal to $420,000) was obtained in the population size of 100 (Fig. 3). After 22 iterations, no change was seen in the cost reduction process in all charts in Fig. 3. While determining the population size, $w = 0.9$, $w_{damp} = 1$ and $c_1 = c_2 = 2$ were selected as default.

The behavior of parameter w was studied by increasing from 0.4 to 0.9 and assuming a population size of 100 (Fig. 4). In $w = 0.4$, minimum network cost ($419,000) was obtained in iteration 23.

After determining the value of w, the optimum value of w_{damp} should be determined. After performing successive iterations of the algorithm, the appropriate range of w_{damp} (0.9–1) is recommended for this network. w_{damp} with its effect on w, caused the optimal solution to be found in fewer iterations. According to Fig. 5, the values of w_{damp} equal to 0.92 and 0.98 had the optimal solution ($419,000) in 13 and 15 iterations, respectively. Compared with the previous state, the number of iterations had a noticeable reduction.

As one can see in Figs. 6 and 7, the investigation was done on c_1 and c_2 within their authorized ranges (4–2) [43]. These two parameters are very sensitive and determining their exact values is time consuming. In Fig. 6, the values of 2.05, 2.3, and 2.45 offer the minimum cost for the parameter c_1, whereas, according to Fig. 7, the values of 2.05 and

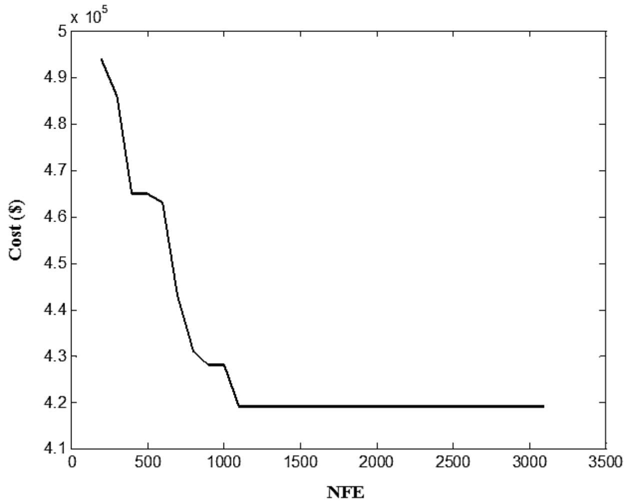

Fig. 2. Convergence chart of SMPSO algorithm in two-loop network optimization.

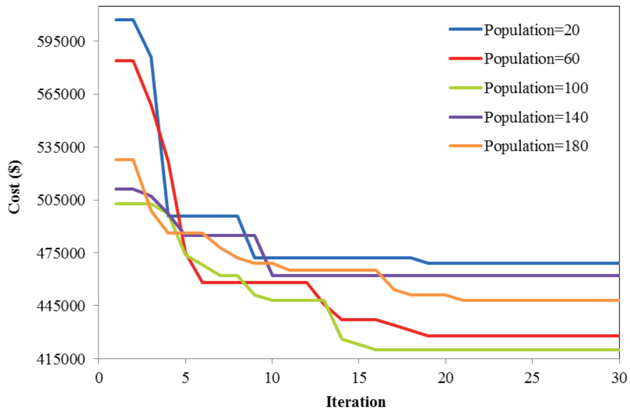

Fig. 3. Changes of population size for the two-loop network.

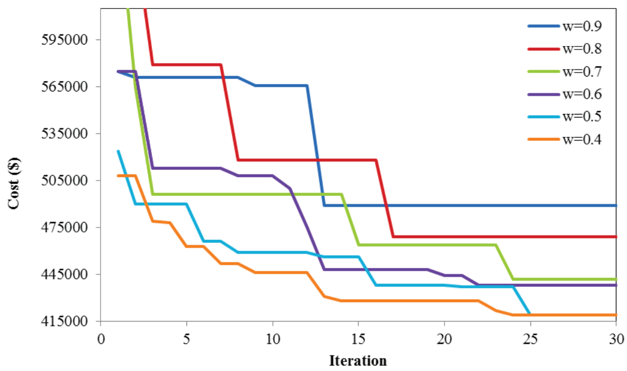

Fig. 4. Changes of w for two-loop network.

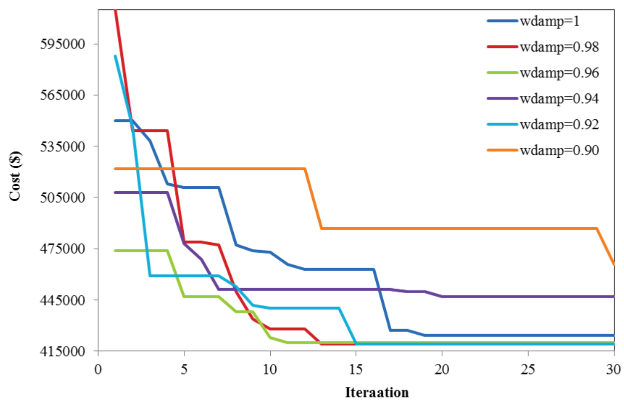

Fig. 5. Changes of w_{damp} for two-loop network.

Table 4
Pipe diameters and node pressures due to optimization with SMPSO method for two-loop network

Pipe number	Diameters (mm)	Node number	Pressure (mH_2O)
1	457.2	2	53.24
2	254	3	30.46
3	406.4	4	43.44
4	101.6	5	33.80
5	406.4	6	30.44
6	254	7	30.55
7	254		
8	25.4		

2.5 are recommended as the best values for parameter c_2. Finally, after examining the combined changes of these two parameters for the two-loop network, it was concluded that $c_1 = c_2 = 2.05$, should be selected.

Finally, the best selected SMPSO input parameters are as follows: population size = 100; $w = 0.4$; $w_{damp} = 0.98$; $c_1 = c_2 = 2.05$ and the maximum number of iterations = 30.

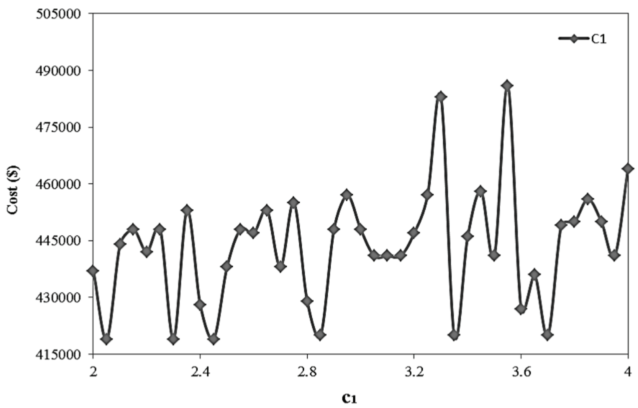

Fig. 6. Changes of c_1 for the two-loop network.

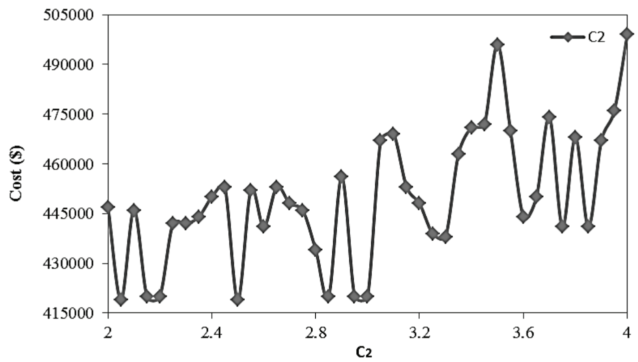

Fig. 7. Changes of c_2 for the two-loop network.

Table 5
Network data for the Hanoi problem

Pipe data	Pipe number	1	2	3	4	5	6	7	8	9	10	11	
	Length (m)	100	1,350	900	1,150	1,450	450	850	850	800	950	1,200	
	Pipe number	12	13	14	15	16	17	18	19	20	21	22	
	Length (m)	3,500	800	500	550	2,730	1,750	800	400	2,200	1,500	500	
	Pipe number	23	24	25	26	27	28	29	30	31	32	33	34
	Length (m)	2,650	1,230	1,300	850	300	750	1,500	2,000	1,600	150	860	950
Node data	Node number	1	2	3	4	5	6	7	8	9	10	11	
	Demand (m^3/h)	–19,940	890	850	130	725	1,005	1,350	550	525	525	500	
	Node number	12	13	14	15	16	17	18	19	20	21	22	
	Demand (m^3/h)	560	940	615	280	310	865	1,345	60	1,275	930	485	
	Node number	23	24	25	26	27	28	29	30	31	32		
	Demand (m^3/h)	1,045	820	170	900	370	290	360	360	105	805		

5.2. Hanoi network

The Hanoi network in Vietnam (Fig. 8), first presented by Fujiwara and Khang [7], is a new design as all new pipes are to be selected. The network consists of 32 nodes and 34 pipes organized in three loops. The system is gravity fed by a single reservoir and network details that are given in Table 5. The minimum required head pressure for all nodes is 30 m. There are six available pipe diameters to be selected for each new pipe; thus, the total search space consists of 6^{34} possible designs. Table 6 lists the pipe cost per meter for the six available pipe diameters.

Table 7 fully shows the results obtained from the SMPSO algorithm in comparison with other algorithms. In SA and HS algorithms, the minimum cost is reported as $\$6.056 \times 10^6$,

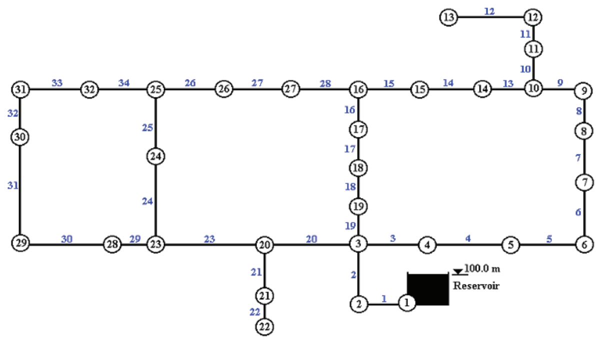

Fig. 8. Layout of Hanoi network.

Table 6
Pipe sizes and costs for Hanoi network

Pipe	Diameter (in)	Cost ($/m)
1	12	45.726
2	16	70.400
3	20	98.378
4	24	129.333
5	30	180.748
6	40	278.280

Table 7
Solutions for Hanoi network obtained by different techniques

Pipe diameters (in)						
Pipe	GA [18]	ACO [48]	SCE [32]	SA [26]	HS [27]	SMPSO (This work)
1	40	40	40	40	40	40
2	40	40	40	40	40	40
3	40	40	40	40	40	40
4	40	40	40	40	40	40
5	40	40	40	40	40	40
6	40	40	40	40	40	40
7	40	40	40	40	40	40
8	40	40	30	40	40	40
9	40	40	30	40	40	40
10	30	30	30	30	30	30
11	24	24	30	24	24	24
12	24	24	24	24	24	24
13	20	20	16	20	20	20
14	16	12	12	16	16	16
15	12	12	12	12	12	12
16	12	12	24	12	12	12
17	16	20	30	16	16	16
18	20	24	30	20	20	24
19	20	20	30	20	20	20
20	40	40	40	40	40	40
21	20	20	20	20	20	20
22	12	12	12	12	12	12
23	40	40	30	40	40	40
24	30	30	30	30	30	30
25	30	30	24	30	30	30
26	20	20	12	20	20	20
27	12	12	20	12	12	12
28	12	12	24	12	12	12
29	16	16	16	16	16	16
30	16	16	16	12	12	16
31	12	12	12	12	12	12
32	12	12	16	16	16	16
33	16	16	20	16	16	16
34	20	20	24	24	24	20
Cost ($ millions)	6.195	6.134	6.220	6.056	6.056	6.097
NFE	1,000,000	85,571	25,402	53,000	200,000	30,300
ω	10.9031	10.667	10.667	10.5088	10.5088	10.667

whereas, ω = 10.5088 and if the solution proposed by these algorithms is simulated by EPANET 2.0 software (ω = 10.667); the least minimum pressure of 30 m was not respected in all nodes [47]. In this network, the cost obtained due to optimization with SMPSO algorithm is $\$6.097 \times 10^6$, obtained after 30,300 times of NFE (Fig. 9). The pressure at each node is shown in Table 8.

Since in Hanoi network the number of network pipes (decision variables) is higher than that of the two-loop network, the initial population size should also increase. Therefore, after reviewing different population sizes in this network, the values of 100, 140, 180, 220, 260, and 300 were evaluated. According to Fig. 10, the population size equal to 300 had a better convergence process. Based on the results of previous example, $c_1 = c_2 = 2.05$ were set in this network first, and then the analysis was performed on other parameters of SMPSO algorithm.

After several times of Hanoi network assessment, it was concluded that the network has many local minimums and solutions, and should be investigated with greater caution by avoiding premature convergence of the algorithm; and w_{damp} values with very little changes in the scope of (0.990–1). As can be seen in Figs. 11 and 12, the best value for w and w_{damp}, were obtained as 0.6 and 0.998, respectively.

After sensitivity analysis, the best SMPSO parameters were chosen as follows: the population size = 300, w = 0.6, w_{damp} = 0.998, $c_1 = c_2$ = 2.05, and the maximum number of iterations = 100.

5.3. Kadu network

A two-reservoir network with 26 nodes, 34 links, and 9 loops is shown in Fig. 13, which was initially introduced and optimized by Kadu et al. [49]. Two reservoirs with heads of 100 and 95 m feed the network through nodes 1 and 2, respectively. Number of nodes, pipes, and demand of each node are shown in cubic meters per minute in Fig. 13; and Hazen–Williams's coefficient is 130 for all pipes. Other information such as the length of pipes and demand of nodes are provided in Table 9. There are 10 commercial diameters, which can be selected to optimize the network that is expressed in Table 10 along with cost per length unit of them. As a result, in this problem, 14^{38} is different states for possible designing, which should be evaluated in the absence of optimization method. In addition, the minimum allowable pressure for network nodes are different values, which leads to more complexity of the problem compared with two previous networks.

This network has already been optimized by GA and GA-ILP (integer-linear programming) algorithms and the minimum cost offered in these methods are 131,312 and 815 rupees that have been obtained after 4,440 times of NFE. In this study, however, SMPSO algorithm obtained 130,666,043 rupees cost after 45,150 times of NFE (Table 11). The maximum NFE increased in comparison with the two previous methods,

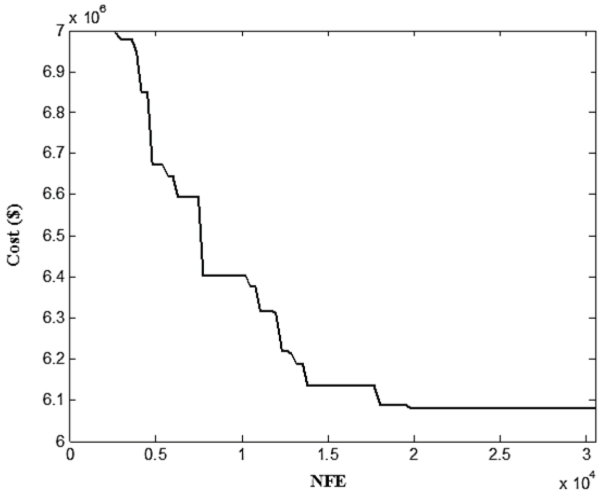

Fig. 9. Convergence chart of SMPSO algorithm in Hanoi network optimization.

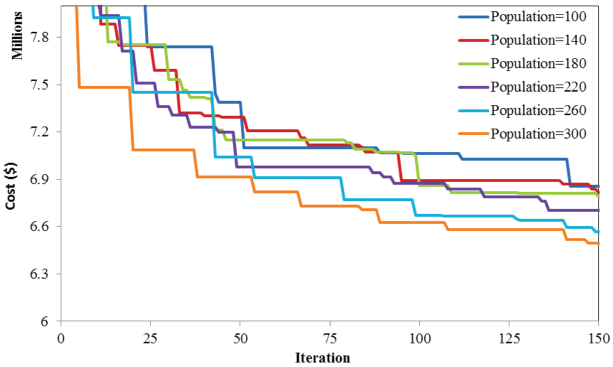

Fig. 10. Changes of population size for Hanoi network.

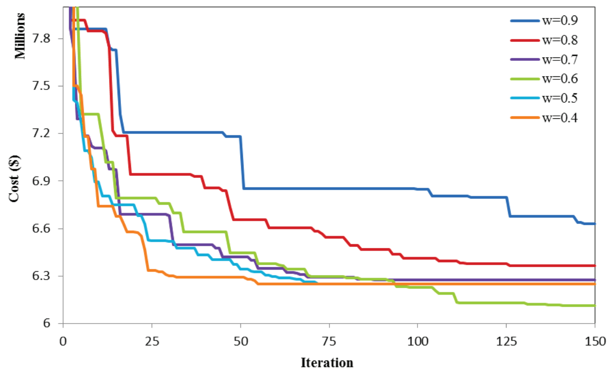

Fig. 11. Changes of w for Hanoi network.

Table 8
Node pressures due to optimization with SMPSO method for Hanoi network

Node number	Pressure (mH_2O)	Node number	Pressure (mH_2O)	Node number	Pressure (mH_2O)
2	97.14	13	30.07	24	39.26
3	61.67	14	35.65	25	36.02
4	56.92	15	33.91	26	32.29
5	51.05	16	31.65	27	31.24
6	44.85	17	33.60	28	35.80
7	43.40	18	49.97	29	31.11
8	41.67	19	55.11	30	30.15
9	40.29	20	50.57	31	30.62
10	39.27	21	41.22	32	31.89
11	37.71	22	36.05		
12	34.28	23	44.44		

but the final cost for the network decreased. Fig. 14 shows that the minimum cost was fixed after 2,200 times of NFE and the algorithm performance is evident on accelerating convergence.

The minimum required pressure and calculated pressure for each node of Kadu network, after optimization with SMPSO, are provided in Table 12. The pressure at each node was higher than the minimum allowable pressure.

The analysis results of the SMPSO parameters on Kadu network are shown in Figs. 15–17.

According to Fig. 15, cost of 180,611,053 rupees were obtained for the network in the population size of 150 and in iteration 270, which is better than other populations. After applying different w, the value $w = 0.4$ was to reduce network cost to 139,444,688 rupees and 130 iterations (Fig. 16). Finally, the minimum cost of 130,666,043 rupees was obtained for Kadu network in iteration 120 by applying $w_{damp} = 0.998$ (Fig. 17).

After optimization of this network with SMPSO algorithm, the final values for its parameters were selected as $w = 0.4$, $c_1 = c_2 = 2.05$, and $w_{damp} = 0.998$. Moreover, the optimization started based on the initial population of 150 and finished after 300 iterations.

6. Summary and conclusions

Designing an optimal WDN is a complex task. Being nonlinear, nonconvex, and discrete in nature make this problem difficult to solve. In general, two major aims are followed in optimizing water pipe networks: (1) obtaining the global solution and (2) developing a computationally efficient procedure [50]. Various deterministic and heuristic algorithms have been proposed and attempted for solving this problem.

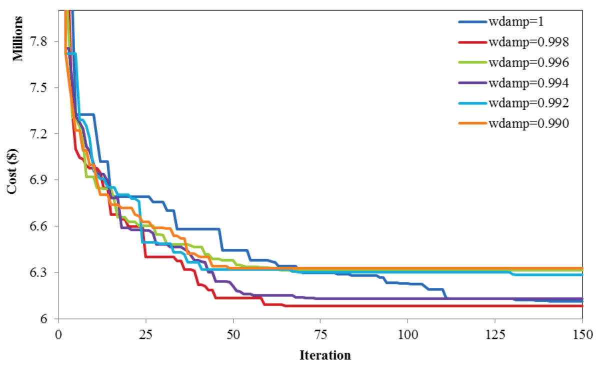

Fig. 12. Changes of w_{damp} for Hanoi network.

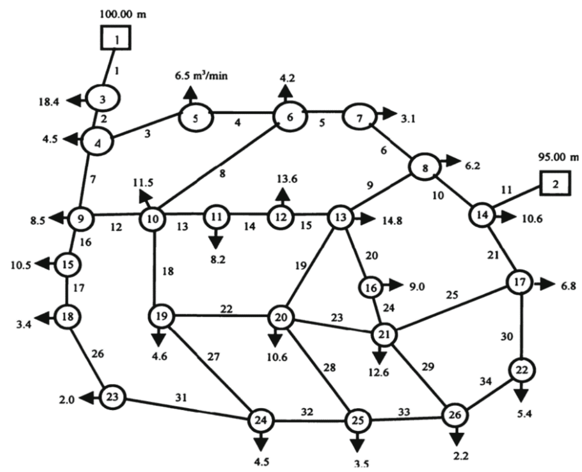

Fig. 13. Layout of Kadu network.

Table 9
Network data for the Kadu network

Pipe data	Pipe number	1	2	3	4	5	6	7	8	9	10	11		
	Length (m)	300	820	940	730	1,620	600	800	1,400	1,175	750	210		
	Pipe number	12	13	14	15	16	17	18	19	20	21	22		
	length (m)	700	310	500	1,960	900	850	650	760	1,100	660	1,170		
	Pipe number	23	24	25	26	27	28	29	30	31	32	33	34	
	Length (m)	980	670	1,080	750	900	650	1,540	730	1,170	1,650	1,320	3,250	
Node data	Node number	1	2	3	4	5	6	7	8	9	10	11	12	13
	Demand (m³/min)	–	–	18.4	4.5	6.5	4.2	3.1	6.2	8.5	11.5	8.2	13.6	14.8
	Node number	14	15	16	17	18	19	20	21	22	23	24	25	26
	Demand (m³/min)	10.6	10.5	9	6.8	3.4	4.6	10.6	12.6	5.4	2	4.5	3.5	2.2

Table 10
Pipe sizes and costs for Kadu network

Pipe number	Diameter (mm)	Cost (rupees/m)	Pipe number	Diameter (mm)	Cost (rupees/m)
1	150	1,115	6	400	4,255
2	200	1,600	7	450	5,172
3	250	2,154	8	500	6,092
4	300	2,780	9	600	8,189
5	350	3,475	10	700	10,670

In this research, a simple modified PSO algorithm, SMPSO, applied for the optimal design of WDN. The minimum cost obtained by SMPSO programming linked via water network hydraulic solver EPANET 2.0. The performance of the proposed SMPSO algorithm studied on three benchmark networks and the results were compared with the previous studies. In a two-loops network, SMPSO obtained the optimal solution in fewer NFE than other stochastic optimization algorithms, including GA, SA, SFLA, HS, and SS.

Table 11
Solutions for the Kadu network obtained by different techniques

Pipe diameters (mm)			
Pipe number	GA-ILP [49]	GA [48]	SMPSO (This work)
1	1,000	1,000	900
2	900	900	900
3	400	400	500
4	350	350	250
5	150	150	150
6	250	250	200
7	800	800	900
8	150	150	150
9	400	400	600
10	500	500	700
11	1,000	1,000	900
12	700	700	700
13	800	800	500
14	400	400	450
15	150	150	150
16	500	500	450
17	350	350	300
18	350	350	450
19	150	150	500
20	150	200	150
21	700	700	600
22	150	150	150
23	450	400	150
24	400	400	400
25	700	700	500
26	250	250	150
27	250	250	350
28	200	200	350
29	300	300	150
30	300	300	300
31	200	200	200
32	150	150	150
33	200	250	200
34	150	150	150
Cost (rupees)	131,312,815	131,678,935	130,666,043
NFE	4,440	360,000	45,150
ω	10.667	10.667	10.667

In the second study case, the Hanoi problem, comparison of the results showed that SMPSO was able to find the best solution in fewer NFEs than other best-performing algorithms, such as SCE and ACO.

In the third example, which was a network offered by Kadu, the complexity of the problem increased due to the

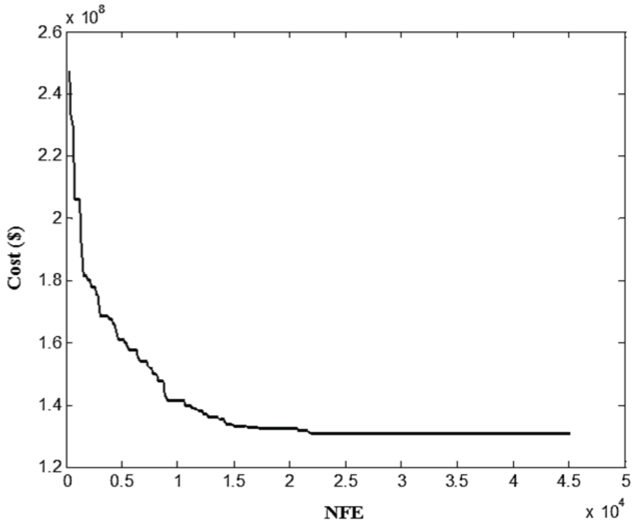

Fig. 14. Convergence chart of SMPSO algorithm in Kadu network.

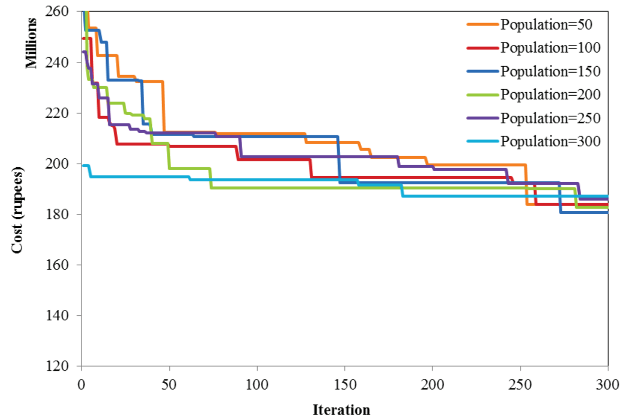

Fig. 15. Changes of population size in Kadu network.

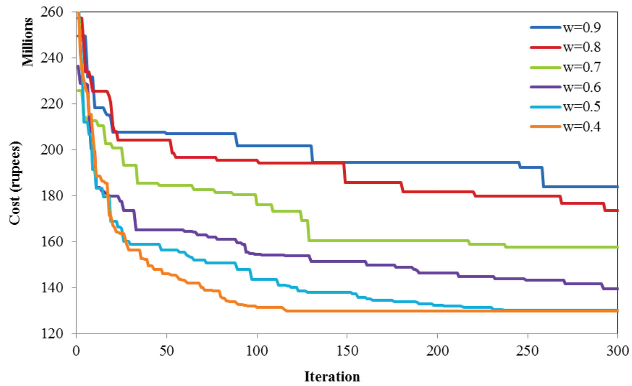

Fig. 16. Changes of w for Kadu network.

Table 12
The node pressures due to optimization with SMPSO method for Kadu network

Node number	Minimum allowable pressure (mH_2O)	Pressure (mH_2O)	Node number	Minimum allowable pressure (mH_2O)	Pressure (mH_2O)	Node number	Minimum allowable pressure (m)	Pressure (mH_2O)
3	85	98.08	11	85	87.86	19	82	87.77
4	85	94.83	12	85	85.88	20	82	84.38
5	85	93.37	13	82	86.41	21	82	84.31
6	85	87.54	14	82	93.97	22	80	85.88
7	82	85.28	15	85	88.43	23	82	82.25
8	82	91.50	16	82	82.39	24	80	85
9	85	92.64	17	82	90.37	25	80	83.32
10	85	89.64	18	85	85.62	26	80	80.46

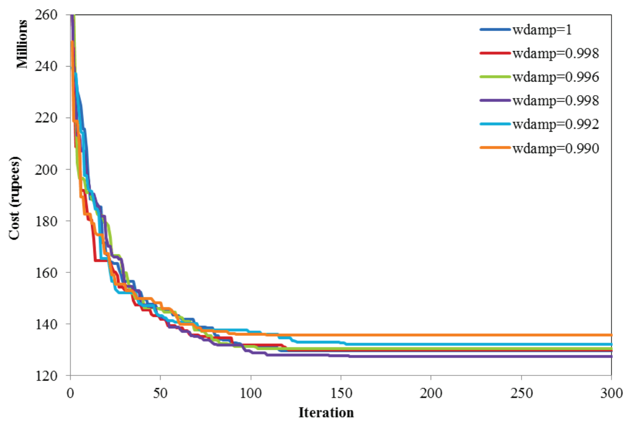

Fig. 17. Changes of w_{damp} for Kadu network.

difference in the minimum allowable pressure of the nodes. The results showed that NFE increased by the proposed SMPSO algorithm, while the least new cost was less than the other previous works.

After the sensitive analysis of the parameters of SMPSO algorithm for all three benchmark networks, the following results were achieved:

1. According to the standard range of w, when it is closer to 0.4, the convergence was accelerated, but if a problem has numerous local minimums such as Hanoi network, it is likely for the algorithm to fall into local minimum trap. Conversely, by increasing the value of w to 0.9, algorithm reviews the solutions with more caution, but the number of iterations will be increased.
2. With increasing the number of decision variables of a problem (i.e., diameter of network pipes), the size of initial population should also increase (e.g., Hanoi and Kadu networks, where the initial population size was more than that of the two-loop network).
3. In the two-loop and Hanoi and Kadu networks, c_1 and c_2 were changed to the amounts suggested by Eberhart (between 2 and 3). After examining all different scenarios, it was concluded that $c_1 = c_2 = 2.05$ are the best values for all the networks in this study.
4. In this research, a new factor called w_{damp} was used to decrease w in each iteration and damp the impact of prior speed on the current speed. This factor was effective in increasing the speed of convergence, and far away from trapping in a local minimum. However, it is better to increase w_{damp} from 0.980 to 0.998 as the network size increases.

Finally, it seems that the SMPSO algorithm can solve optimization problems of WDNs with a few parameters and easy implementation. It also can find the optimal solution in less duration than other algorithms.

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