

# Cost optimization of water distribution networks by using artificial immune systems

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## ABSTRACT

This study aims at the development of an optimization model based on artificial immune systems (AIS) to minimize cost designs of water distribution networks (WDNs). Clonal selection algorithm (Clonalg), a class of AIS, was used as an optimization technique in the model, and its mutation operation was modified to increase the diversity (search capability). EPANET, a widely known WDN simulator, was used in conjunction with the proposed model. The model was applied to four WDNs of Two-loop, Hanoi, Go Yang, New York City, and the results obtained were compared with other heuristic and mathematical optimization models in the related literature, such as harmony search, genetic algorithm, immune algorithm, shuffled complex evolution, differential evolution, and non-linear programming-Lagrangian algorithm. Furthermore, the modified Clonalg was compared with the classic Clonalg in order to demonstrate the impact of the modification on the diversity. The proposed model appeared to be promising in terms of cost designs of WDNs.

**Key words** | artificial immune systems, optimization, water distribution network

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## INTRODUCTION

At the present time, design engineers should consider the cost and functionality while designing any project. In this regard, cost optimization techniques are mostly used in the designing of water distribution networks (WDNs). Many conventional optimization techniques have been developed to solve minimal-cost problems, such as linear programming gradient (Alperovits & Shamir 1977; Fujiwara *et al.* 1987; Kessler & Shamir 1989; Bhave & Sonak 1992; Eiger *et al.* 1994), dynamic programming (Schaake & Lai 1969), and non-linear programming (NLP) (Fujiwara & Khang 1990; Varma *et al.* 1997). However, obtaining a least-cost WDN with discrete-value pipe diameters is extremely difficult using conventional optimization techniques (Yates *et al.* 1984). On the other hand, heuristic algorithms have recently been utilized to solve WDN optimization problems, such as genetic algorithm (GA), simulated

annealing, Tabu search, ant colony optimization, scatter search, shuffled complex evolution (SCE), and differential evolution (DE) (Simpson *et al.* 1994; Cunha & Sousa 1999; Maier *et al.* 2003; Cunha & Ribeiro 2004; Liong & Atiquzzaman 2004; Zecchin *et al.* 2006; Lin *et al.* 2007; Dong *et al.* 2012). Geem (2006), Savic & Walters (1997), and Kim *et al.* (1994) proposed cost optimization models using a harmony search (HS) algorithm, GA, and a projected Lagrangian algorithm (NLP), respectively, for the following four famous WDN problems of Two-loop, Hanoi, Go Yang, and New York City in the related literature. Another heuristic algorithm is artificial immune systems (AIS) simulating the natural immune system (NIS) (Harmer *et al.* 2002; De Castro & Timmis 2003; Koster *et al.* 2003; Bezerra *et al.* 2004). AIS have been successfully applied to various test functions and optimization

problems (Tazawa *et al.* 1996; Hajela *et al.* 1997; Chu *et al.* 2008).

This study develops a cost optimization model based on AIS in order to contribute to the related literature. The model aims to determine optimal diameters of pipes in WDNs under hydraulic conditions such as water demand, and minimum pressure requirement. Clonal selection algorithm (Clonalg), a class of AIS, was used as an optimization technique in the model in order to minimize the cost designs of WDNs. The main difference to the classic Clonalg, is the modification proposed to its mutation operation. While running the algorithm, new genes were generated for each antibody during the mutation operation instead of generating new individuals (antibody) in each iteration. This modification provides to increase a diversity. The model was applied to the four benchmark WDNs, and results obtained were compared with the other algorithms in the

related literature, such as HS, GA, NLP, immune algorithm (IA), SCE, and DE. Furthermore, the modified Clonalg was compared with the classic Clonalg in order to demonstrate the impact of the modification on the diversity.

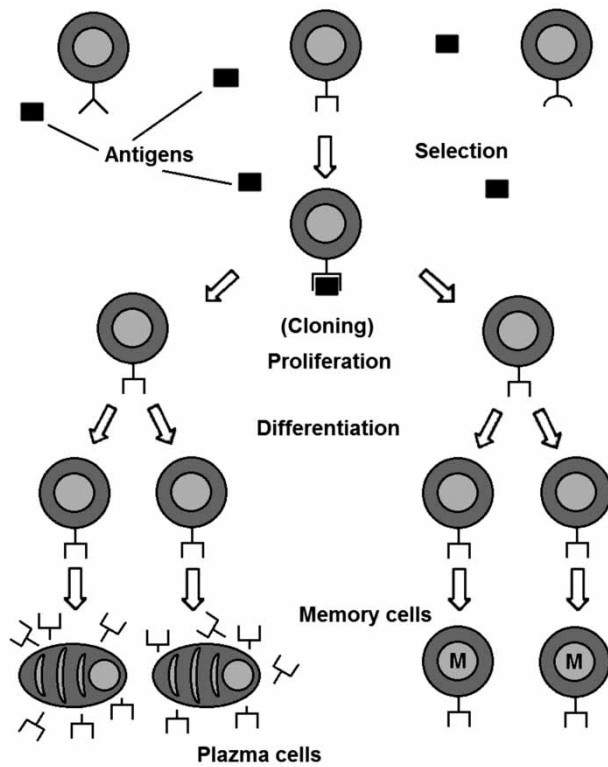


Figure 1 | Clonal Selection Theory (De Castro & Von Zuben 2000).

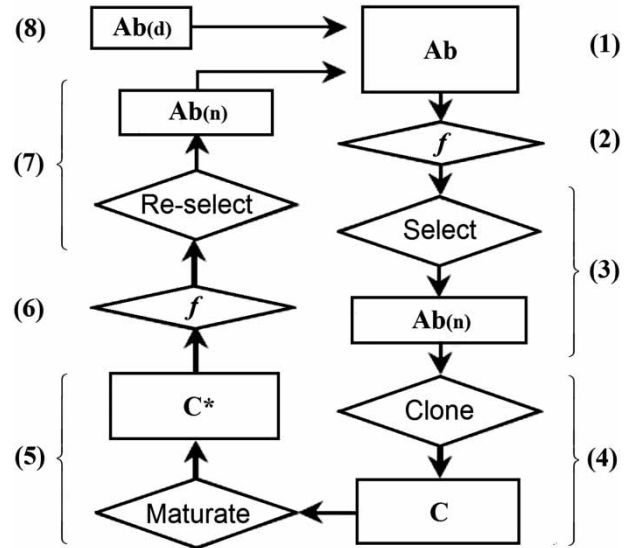


Figure 2 | Flow chart of Clonalg for optimization (De Castro & Von Zuben 2002).

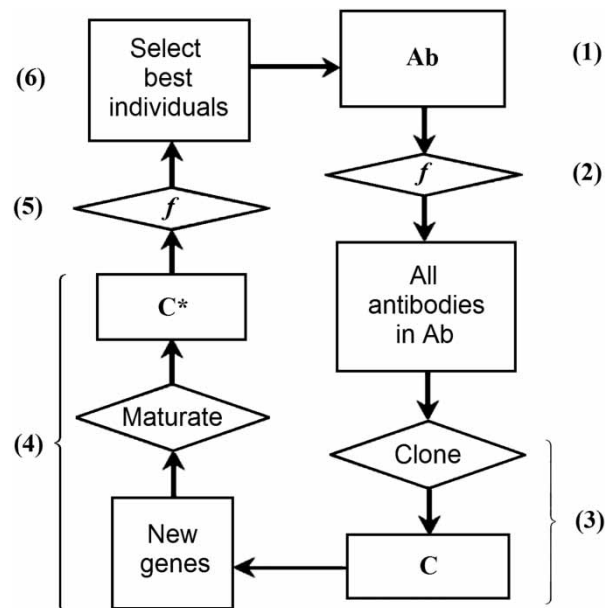


Figure 3 | Flow chart of the modified Clonalg for optimization.

**Table 1** | Candidate diameters and corresponding costs for the networks

Network	Candidate Diameter	Corresponding Cost
Two-loop	1, 2, 3, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22, 24 in inches	2, 5, 8, 11, 16, 23, 32, 50, 60, 90, 130, 170, 300, 550 in USD/meter
Hanoi	12, 16, 20, 24, 30, 40 in inches	45.726, 70.4, 98.378, 129.333, 180.748, 278.28 in USD/meter
New York	0, 36, 48, 60, 72, 84, 96, 108, 120, 132, 144, 156, 168, 180, 192, 204 in inches	93.5, 134, 176, 221, 267, 316, 365, 417, 469, 522, 577, 632, 689, 746, 804 in USD/foot
GoYang	80, 100, 125, 150, 200, 250, 300, 350 in millimeters	37,890, 38,933, 40,563, 42,554, 47,624, 54,125, 62,109, 71,524 in won/meter

## CLONALG

AIS are based on the principles of the NIS. There are two selection theories of ‘Clonal Selection Theory’ and ‘Negative Selection Theory’, involving these principles in the immune system. Clonalg, a class of AIS, is based on Clonal Selection Theory (De Castro & Von Zuben 2000, 2002). This theory uses the following three major principles of Charles Darwin’s law of evolution: diversity, variation, and natural selection (De Castro & Von Zuben 2002). Figure 1 illustrates the Clonal Selection Theory.

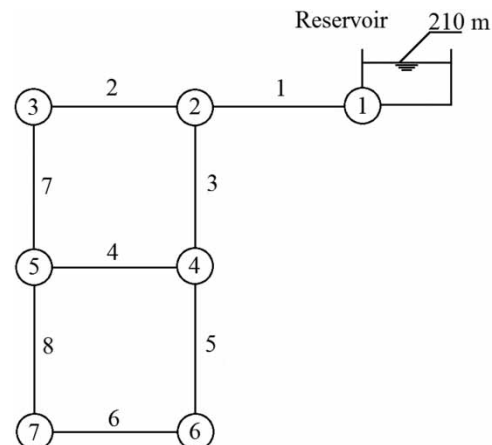
Clonalg can be described for optimization problems as follows (De Castro & Von Zuben 2002):

- (1) An antibody set ( $Ab$ ) is randomly constituted and there is an objective function  $g(\cdot)$  to be optimized (maximized or minimized). An antibody’s antigenic affinity corresponds to the value of this objective function for a given antibody, so that each antibody ( $Ab_i$ ) represents an element of the input set ( $Ab$ ).
- (2) For each  $Ab_i$  in  $Ab$ , the affinity value ( $f_i$ ) is determined.
- (3) The  $n$  amount of antibodies with the highest affinity is selected.
- (4) The  $n$  amount of antibodies selected is cloned (reproduced) independently and proportionally to their antigenic affinities. The clones constitute a repertoire  $C$ . The higher antigenic affinity means the higher number of clones generated for each of the  $n$  antibodies.

- (5) The repertoire  $C$  is exposed to an affinity maturation process (mutation) inversely proportional to the antigenic affinity. The matured clones constitute a

**Table 2** | Node and pipe data of Two-loop network

Node	Elevation (m)	Demand ( $m^3/h$ )	Min. Pressure (m)	Pipe	Length (m)	C
1	210	Reservoir	Reservoir	1	1000	130
2	150	100	30	2	1000	130
3	160	100	30	3	1000	130
4	155	120	30	4	1000	130
5	150	270	30	5	1000	130
6	165	330	30	6	1000	130
7	160	200	30	7	1000	130
				8	1000	130

**Figure 4** | Layout of Two-loop network.

population  $C^*$ . The higher antigenic affinity means a smaller mutation rate.

- (6) For each matured clone in  $C^*$ , the affinity value ( $f_i^*$ ) is determined.

- (7) From the population  $C^*$ , the  $n$  amount of the matured clones with the highest affinity is reselected and added to  $Ab$ .
- (8) Finally, the  $d$  amount of the antibodies with the lowest affinity is replaced with new individuals ( $Ab_d$ ).

Figures 2 and 3 illustrate the flow charts of the classic Clonalg and the modified Clonalg for optimization problems, respectively.

Description of  $Ab$

$$\begin{matrix}
 \overbrace{\left[ \begin{matrix} Ab_1 & x_{11} & \cdots & x_{1j} & \cdots & x_{1nd} \\ \vdots & \vdots & & & & \vdots \\ Ab_i & x_{i1} & & \ddots & & x_{ind} \\ \vdots & \vdots & & & & \vdots \\ Ab_{N_{Ab}} & x_{N_{Ab}1} & \cdots & x_{N_{Ab}j} & \cdots & x_{N_{Ab}nd} \end{matrix} \right]}^{Ab} \\
 \rightarrow \left[ \begin{matrix} f_1 \\ \vdots \\ f_i \\ \vdots \\ f_{N_{Ab}} \end{matrix} \right] \quad i = 1, \dots, N_{Ab} \quad j = 1, \dots, nd \quad (1)
 \end{matrix}$$

where  $N_{Ab}$  is the total number of the antibodies in  $Ab$ ,  $x_{ij}$  is the gene of  $Ab_i$ , corresponding to a variable of

Table 3 | Node and pipe data of Hanoi network

Node	Elevation (m)	Demand (m <sup>3</sup> /h)	Min. Pressure (m)	Pipe	Length (m)	C
1	100	Reservoir	Reservoir	1	100	130
2	0	890	30	2	1350	130
3	0	850	30	3	900	130
4	0	130	30	4	1150	130
5	0	725	30	5	1450	130
6	0	1005	30	6	450	130
7	0	1350	30	7	850	130
8	0	550	30	8	850	130
9	0	525	30	9	800	130
10	0	525	30	10	950	130
11	0	500	30	11	1200	130
12	0	560	30	12	3500	130
13	0	940	30	13	800	130
14	0	615	30	14	500	130
15	0	280	30	15	550	130
16	0	310	30	16	2730	130
17	0	865	30	17	1750	130
18	0	1345	30	18	800	130
19	0	60	30	19	400	130
20	0	1275	30	20	2200	130
21	0	930	30	21	1500	130
22	0	485	30	22	500	130
23	0	1045	30	23	2650	130
24	0	820	30	24	1230	130
25	0	170	30	25	1300	130
26	0	900	30	26	850	130
27	0	370	30	27	300	130
28	0	290	30	28	750	130
29	0	360	30	29	1500	130
30	0	360	30	30	2000	130
31	0	105	30	31	1600	130
32	0	805	30	32	150	130
				33	860	130
				34	950	130

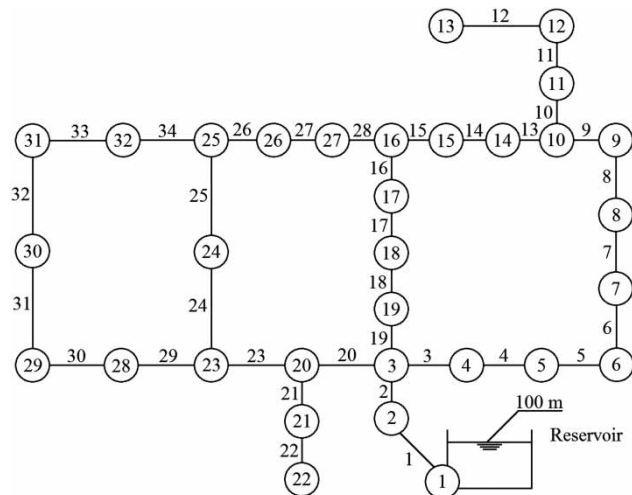


Figure 5 | Layout of Hanoi network.

the objective function, and  $nd$  is the number of genes of  $Ab_i$ . In this study,  $x_{ij}$  corresponds to a diameter of the pipe.

The number of clones generated for all the  $n$  selected antibodies can be estimated as follows (De Castro & Von Zuben 2002):

$$N_c = \sum_{i=1}^n \text{round}\left(\frac{\beta \cdot N_{Ab}}{i}\right) \quad i = 1, \dots, n \quad (2)$$

where  $N_c$  is the total number of the clones in  $C$ ,  $\beta$  is a multiplying coefficient, 'round' is the rounding operator for an integer.

The mutation rate can be computed as follows (De Castro & Von Zuben 2002):

$$\alpha_i = \exp(-\rho \cdot f_i) \quad (3)$$

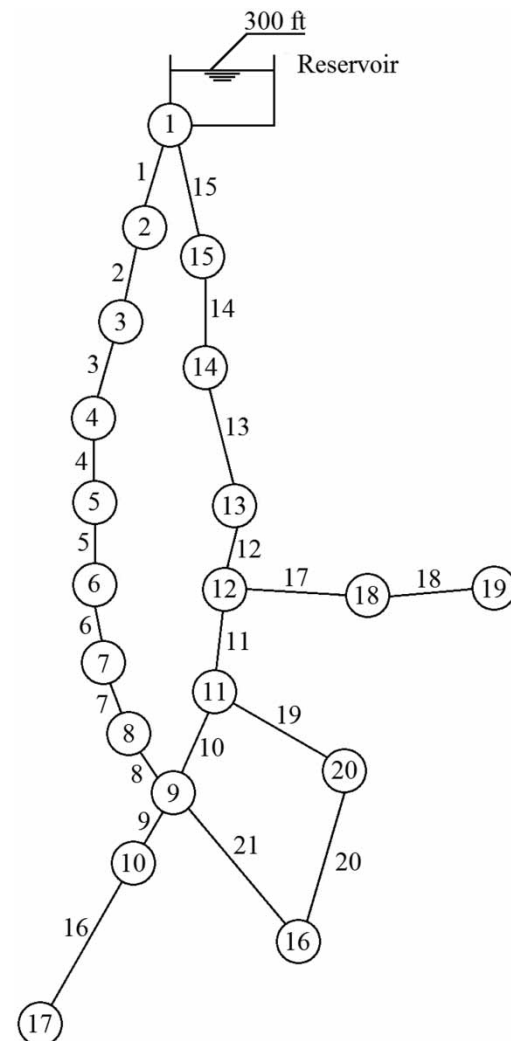
**Table 4** | Node and pipe data of New York City network

Node	Demand (cfs)	Min. Head (ft)	Pipe	Length (ft)	c
1	Reservoir	Reservoir	1	11,600	100
2	92.4	255.0	2	19,800	100
3	92.4	255.0	3	7300	100
4	88.2	255.0	4	8300	100
5	88.2	255.0	5	8600	100
6	88.2	255.0	6	19,100	100
7	88.2	255.0	7	9600	100
8	88.2	255.0	8	12,500	100
9	170.0	255.0	9	9600	100
10	1.0	255.0	10	11,200	100
11	170.0	255.0	11	14,500	100
12	117.1	255.0	12	12,200	100
13	117.1	255.0	13	24,100	100
14	92.4	255.0	14	21,100	100
15	92.4	255.0	15	15,500	100
16	170.0	260.0	16	26,400	100
17	57.5	272.8	17	31,200	100
18	117.1	255.0	18	24,000	100
19	117.1	255.0	19	14,400	100
20	170.0	255.0	20	38,400	100
			21	26,400	100

where  $\alpha_i$  is the mutation rate for the clones exposed to the maturation process,  $\rho$  is a decay coefficient, and  $f_i$  is the affinity value normalized over the interval [0,1].

In this study, new genes are generated for each clone with a certain probability depending on a given problem (probability rate) in step 5, instead of step 8. This modification provides to increase the diversity. Furthermore, instead of using Equation (2) as proposed by De Castro & Von Zuben (2002), the following equation was used to calculate  $N_c$  (De Castro & Von Zuben 2002):

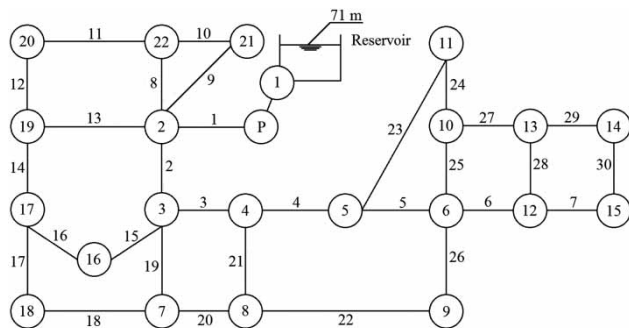
$$N_c = \sum_{i=1}^{N_{Ab}} \text{round}(\beta \cdot N_{Ab}) \quad i = 1, \dots, N_{Ab} \quad (4)$$



**Figure 6** | Layout of New York network.

**Table 5** | Node and pipe data of Go Yang network

Node	Elevation (m)	Demand (m <sup>3</sup> /day)	Min. Pressure (m)	Pipe	Length (m)	C
1	71.0	Reservoir	Reservoir	1	165	100
2	56.4	153.0	15	2	124	100
3	53.8	70.5	15	3	118	100
4	54.9	58.5	15	4	81	100
5	56.0	75.0	15	5	134	100
6	57.0	67.5	15	6	135	100
7	53.9	63.0	15	7	202	100
8	54.5	48.0	15	8	135	100
9	57.9	42.0	15	9	170	100
10	62.1	30.0	15	10	113	100
11	62.8	42.0	15	11	335	100
12	58.6	37.5	15	12	115	100
13	59.3	37.5	15	13	345	100
14	59.8	63.0	15	14	114	100
15	59.2	445.5	15	15	103	100
16	53.6	108.0	15	16	261	100
17	54.8	79.5	15	17	72	100
18	55.1	55.5	15	18	373	100
19	54.2	118.5	15	19	98	100
20	54.5	124.5	15	20	110	100
21	62.9	31.5	15	21	98	100
22	61.8	799.5	15	22	246	100
				23	174	100
				24	102	100
				25	92	100
				26	100	100
				27	130	100
				28	90	100
				29	185	100
				30	90	100



**Figure 7** | Layout of Go Yang network.

**Table 6** | Parameters of the modified Clonalg and the classic Clonalg for Two-loop network

Algorithm	$\omega$	$N_{Ab}$	$\beta$	$\rho$	Probability Rate	Max. Iteration
Modified	10.4973	150	0.02	2	0.25	500
	10.5088	150	0.02	2	0.25	500
	10.667	150	0.1	2	0.25	500
Classic	10.667	150	0.1	2	-	500

**Table 7** | Comparison of the results for Two-loop network

Pipe	Modified Clonalg (This study)			HS Geem (2006)		GA Keedwell & Khu (2005)	GA Savic & Walters (1997)
	$\omega = 10.4973$	$\omega = 10.5088$	$\omega = 10.667$	$\omega = 10.4973$	$\omega = 10.5879$	$\omega = 10.667$	$\omega = 10.5088$
1	18	18	18	18	18	18	18
2	10	10	10	10	10	10	10
3	16	16	16	16	16	16	16
4	4	4	4	4	4	4	4
5	16	16	16	16	16	16	16
6	10	10	10	10	10	10	10
7	10	10	10	10	10	10	10
8	1	1	1	1	1	1	1
Cost(\$)	419,000	419,000	419,000	419,000	419,000	419,000	419,000

This modification results in that both all antibodies in  $Ab$  are cloned and the same number of the clones is generated for each antibody in  $Ab$ . Thus, there is not any selection of  $n$  amount of antibodies with the highest affinity (step 3).

## MODEL FORMULATION

The cost design of WDNs consists of diameters and lengths of pipes constituting the network. Thus, the objective function depends on the pipe's diameter and length. The objective function used in the model is of the following form (Geem 2006; Chu *et al.* 2008):

$$C = \sum_{i=1}^N f(D_i, L_i) \quad i = 1, \dots, N \quad (5)$$

where  $f(D_i, L_i)$  is the cost of pipe  $i$  with its diameter  $D_i$  and length  $L_i$ , and  $N$  is the number of pipes in the network. While determining the diameters, the hydraulic conditions of water demands and minimum pressures required at all the junction nodes of the WDN should be satisfied. In this regard, the cost function is to be minimized by considering the following constraints (Geem 2006; Chu *et al.* 2008).

For each node, the continuity equation should be satisfied

$$\sum Q_{in} - \sum Q_{out} = Q_e \quad (6)$$

where  $Q_{in}$  and  $Q_{out}$  are the inflow and outflow rate of the node, respectively, and  $Q_e$  is the external inflow rate or demand at the node.

For each loop in the network, the energy conservation equation is utilized

$$\sum_{i=1}^N \Delta H_i - E_p = 0 \quad i = 1, \dots, N \quad (7)$$

**Table 8** | Comparison of the modified Clonalg and the classic Clonalg for Two-loop network

Pipe	Modified Clonalg	Classic Clonalg
	$\omega = 10.667$	$\omega = 10.667$
1	18	18
2	10	10
3	16	16
4	4	4
5	16	16
6	10	10
7	10	10
8	1	1
Cost (won)	419,000	419,000

**Table 9** | Performances of the modified Clonalg and the classic Clonalg for Two-loop network

Algorithm	$\omega$	Min. Cost (USD)	Max. Cost (USD)	Success rate in 20 runs (%)	Average Run Time (min)	Average Iteration Number
Modified	10.4973	419,000	419,000	100	5.5	448
	10.5088	419,000	419,000	100	6	486
	10.667	419,000	420,000	95	8	116
Classic	10.667	419,000	459,000	15	0.7	124

where  $\Delta H_i$  is the head loss in pipe  $i$ , and  $E_p$  is the energy added to the water in the network by a pump.

For each node, the minimum pressure required is expressed as follows:

$$H_j \geq H_j^{\min} \quad j = 1, \dots, M \quad (8)$$

where  $H_j$  is the pressure head at node  $j$ ,  $H_j^{\min}$  is the minimum required pressure head at node  $j$ , and  $M$  is the number of nodes in the network.

The model uses EPANET for the hydraulics analysis. EPANET has three head loss equations – Hazen–Williams, Darcy–Weisbach and Chezy–Manning – to compute the friction head loss in the pipes. The Hazen–Williams equation

was used in this study (Rossman 2000)

$$\Delta H = 4.727C^{-1.852}Q^{1.852}D^{-4.871}L \quad (9)$$

where  $\Delta H$  is the head loss (length; ft or m),  $C$  is Hazen–Williams roughness coefficient,  $Q$  is the flow rate (volume/time; cfs),  $D$  is the pipe diameter (ft), and  $L$  is the pipe length (ft).

Savic & Walters (1997) introduced a numerical conversion constant depending on the units used. With this constant, the Hazen–Williams equation can be re-arranged as follows:

$$\Delta H = \omega \frac{L}{C^\alpha D^\beta} Q^\alpha \quad (10)$$

**Table 10** | Pressures at the nodes of Two-loop network

Node	Pressures (m)		
	$\omega = 10.4973$	$\omega = 10.5088$	$\omega = 10.667$
1	Reservoir	Reservoir	Reservoir
2	53.35	53.34	53.24
3	30.77	30.75	30.46
4	43.63	43.62	43.44
5	34.22	34.19	33.80
6	30.67	30.66	30.44
7	30.86	30.84	30.55

**Table 11** | Parameters of the modified Clonalg and the classic Clonalg for Hanoi network

Algorithm	$\omega$	$N_{Ab}$	$\beta$	$\rho$	Probability Rate	Max. Iteration
Modified	10.5088	30	0.05	1.7	0.01	20,000
	10.667	40	2	1.7	0.01	500
Classic	10.667	40	2	1.7	–	1000



**Table 12** | Comparison of the results for Hanoi network

Pipe	Modified Clonalg (This study)		Van Dijk <i>et al.</i> (2008)	HS Geem (2006)	Wu & Walski (2005)	Liong & Atiquzzaman (2004)	Vairavamoorthy & Ali (2000)	GA Savic & Walters (1997)
	$\omega = 10.5088$	$\omega = 10.667$	$\omega = 10.667$	$\omega = 10.5088$	$\omega = 10.667$	$\omega = 10.667$	$\omega = 10.5088$	$\omega = 10.5088$
1	40	40	40	40	40	40	40	40
2	40	40	40	40	40	40	40	40
3	40	40	40	40	40	40	40	40
4	40	40	40	40	40	40	40	40
5	40	40	40	40	40	40	40	40
6	40	40	40	40	40	40	40	40
7	40	40	40	40	40	40	40	40
8	40	40	40	40	40	30	40	40
9	30	40	40	40	40	30	40	40
10	30	30	30	30	30	3	30	30
11	24	24	24	24	24	30	24	24
12	24	24	24	24	24	24	24	24
13	16	20	24	20	20	16	20	20
14	12	16	12	16	16	12	16	16
15	12	12	12	12	12	12	12	12
16	12	12	12	12	12	24	12	12
17	20	16	16	16	16	30	16	16
18	20	24	24	20	20	30	20	20
19	24	20	24	20	20	30	20	20
20	40	40	40	40	40	40	40	40
21	20	20	20	20	20	20	20	20
22	12	12	12	12	12	12	12	12
23	40	40	40	40	40	30	40	40
24	30	30	30	30	30	30	30	30
25	30	30	30	30	30	24	30	30
26	20	20	20	20	20	12	20	20
27	16	12	12	12	12	20	12	12
28	12	12	12	12	12	24	12	12
29	16	16	16	16	16	16	16	16
30	12	12	12	12	12	16	12	16
31	12	12	12	12	12	12	12	12
32	20	16	20	16	16	16	16	12
33	16	16	16	16	16	20	16	16
34	24	24	24	24	24	24	24	20
Cost(\$)	6,016,520	6,081,087	6,110,000	6,056,000	6,056,000	6,220,000	6,056,000	6,073,000

**Table 13** | Comparison of the modified Clonalg and the classic Clonalg for Hanoi network

Pipe	Modified Clonalg	Classic Clonalg
	$\omega = 10.667$	$\omega = 10.667$
1	40	40
2	40	40
3	40	40
4	40	40
5	40	40
6	40	40
7	40	40
8	40	40
9	40	40
10	30	30
11	24	24
12	24	24
13	20	20
14	16	16
15	12	12
16	12	12
17	16	16
18	24	24
19	20	20
20	40	40
21	20	20
22	12	12
23	40	40
24	30	30
25	30	30
26	20	20
27	12	12
28	12	12
29	16	16
30	12	12
31	12	12
32	16	20
33	16	16
34	24	24
Cost (\$)	6,081,087	6,085,284

where  $\omega$  is a conversion constant,  $\alpha$  is a coefficient equal to 1.852 (Rossman 2000), and  $\beta$  is a coefficient equal to 4.871 (Rossman 2000). While considering the minimum

pressure head requirements, the higher constant  $\omega$  values require a larger diameter to deliver the same amount of water than the lower values since the greater head loss means higher cost for the WDN designs (Geem 2006). The constant  $\omega$  value in EPANET v.2.0 is 10.667 (Eusuff 2004; Van Dijk *et. al* 2008). This value  $\omega$  can be derived as follows (Rossman 2000; Reehuis 2010):

$$\omega = \frac{\text{conv}Q^\alpha}{\text{conv}D^\beta} 4.727$$

where convQ is a conversion factor from defined unit for Q to cfs, and convD is a conversion factor from defined unit for D to ft. When Q and D are expressed in m<sup>3</sup>/s and m, respectively, and  $\omega$  becomes:

$$\omega = \frac{\text{conv}Q^{1.852}}{\text{conv}D^{4.871}} 4.727 = 10.667$$

where:

$$\text{conv}Q = 35.31466 \text{ m}^3/\text{s} \rightarrow \text{cfs}$$

$$\text{conv}D = 3.28083 \text{ m} \rightarrow \text{ft.}$$

The penalty function is described in addition to the objective function in case of violating the constraints. This function prevents searching from taking place in the infeasible solution space where pipes with small diameters that cannot satisfy the minimum pressure requirement at each node are located. The penalty function is of the following form (Geem 2006):

$$f_p(H_j) = a \left\{ \max(0, H_j^{\min} - H_j) \right\}^2 + b \text{sgn} \left\{ \max(0, H_j^{\min} - H_j) \right\}$$

where  $f_p$  is the penalty function, max is the maximum function giving the larger value, sgn is the sign function extracting the sign of a real number, and  $a$  and  $b$  are the penalty coefficients. The penalty function is added to the total design cost  $C_t$ :

$$C_t = \sum_{i=1}^N f(D_i, L_i) + \sum_{j=1}^M f_p(H_j)$$

**Table 14** | Performances of the modified Clonalg and the classic Clonalg for Hanoi network

Algorithm	$\omega$	Min. Cost (USD)	Max. Cost (USD)	Success rate in 20 runs (%)	Average Run Time (min)	Average Iteration Number
Modified	10.5088	6,016,520	6,025,984	95	141	20,000
	10.667	6,081,087	6,089,927	90	271.6	500
Classic	10.667	6,085,284	6,431,702	5	37.8	1000

**Table 15** | Pressures at the nodes of Hanoi network

Node	Pressures (m)	
	$\omega = 10.5088$	$\omega = 10.667$
1	Reservoir	Reservoir
2	97.18	97.14
3	62.24	61.67
4	57.84	56.92
5	52.40	51.02
6	46.70	44.81
7	45.38	43.35
8	43.84	41.61
9	42.63	40.23
10	39.07	39.20
11	37.53	37.64
12	34.16	34.21
13	30.01	30.01
14	32.37	35.52
15	30.08	33.72
16	30.04	31.30
17	38.56	33.41
18	45.54	49.93
19	59.28	55.09
20	50.99	50.61
21	41.78	41.26
22	36.70	36.10
23	44.70	44.52
24	38.81	38.93
25	34.94	35.34
26	30.56	31.70
27	30.06	30.76
28	39.10	38.94
29	30.13	30.13
30	30.35	30.42
31	30.45	30.70
32	32.84	33.18

## APPLICATIONS

The model was applied to four benchmark WDNs. The commercial diameters and their corresponding costs used in the applications are given in [Table 1](#).

### Two-loop water distribution network

This network consists of seven nodes and eight pipes with two loops, and is fed by the gravity from a reservoir with a 210 m fixed head ([Alperovits & Shamir 1977](#)). Node and pipe data and the layout of Two-loop network are shown in [Table 2](#) and [Figure 4](#), respectively.

### Hanoi water distribution network

This network consists of 32 nodes, 34 pipes and three loops, and is fed by the gravity from a reservoir with a 100 m fixed head ([Fujiwara & Khang 1990](#)). Node and pipe data and the layout of Hanoi network are shown in [Table 3](#) and [Figure 5](#), respectively.

### New York City water distribution network

This network consists of 20 nodes, 21 pipes and one loop, and is fed by the gravity from a reservoir with a 300 ft

**Table 16** | Parameters of the modified Clonalg and the classic Clonalg for New York City network

Algorithm	$\omega$	$N_{Ab}$	$\beta$	$\rho$	Probability Rate	Max. Iteration
Modified	10.5088	100	0.02	2.4	0.1	1000
	10.667	100	0.1	2.4	0.1	500
Classic	10.667	300	1	2	–	500

fixed head. The objective of the problem is to add new pipes parallel to existing pipes in the network since the existing pipes cannot satisfy the pressure head requirements at nodes 16, 17, 18, 19, and 20 (Schaake & Lai 1969). Node and pipe data and the layout of the New York City network are shown in Table 4 and Figure 6, respectively.

### Go Yang water distribution network

This network consists of 22 nodes, 30 pipes and nine loops, and is fed by a pump from a reservoir with a 71 m fixed head (Kim *et al.* 1994). The pressure head produced by the pump is 15.61 m so that the total head of the water supplied from the reservoir becomes 86.61 m. Node and pipe data and the

layout of Go Yang network are shown in Table 5 and Figure 7, respectively.

## RESULTS

The following two conditions were used to stop running the model: (1) when the absolute error between the maximum and minimum values of the objective function is less than 0.1; and (2) when the maximum iteration number is reached.

The model was run 20 times for each WDN. Random seed (random number generation) was applied while constituting the initial set in each run. In the applications of the

**Table 17** | Comparison of the results for New York City network

Pipe	Modified Clonalg (This study)		IA Chu <i>et al.</i> (2008)	Van Dijk <i>et al.</i> (2008)	HS Geem (2006)	Montesinos <i>et al.</i> (1999)	GA Savic & Walters (1997)
	$\omega = 10.5088$	$\omega = 10.667$	$\omega = 10.5088$	$\omega = 10.667$	$\omega = 10.5088$	$\omega = 10.667$	$\omega = 10.5088$
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0
7	96	144	108	144	96	0	108
8	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0
15	0	0	0	0	0	120	0
16	96	96	96	96	96	84	96
17	96	96	96	96	96	96	96
18	84	84	84	84	84	84	84
19	72	72	72	72	72	72	72
20	0	0	0	0	0	0	0
21	72	72	72	72	72	72	72
Cost (\$)	36,660,000	38,637,600	37,130,000	38,637,600	36,660,000	38,800,000	37,130,000

classic Clonalg,  $n$  and  $d$  were assigned as 90% of  $N_{Ab}$  and 10% of  $N_{Ab}$ , respectively, since De Castro & Von Zuben (2002) suggested that values of  $d$  range from 5 to 20% of  $N_{Ab}$  (population).

In the study, a PC with Intel Core Duo 2.16 Ghz and Matlab R2009a 7.8 programming language were used for

**Table 18** | Comparison of the modified Clonalg and the classic Clonalg for New York City network

Pipe	Modified Clonalg	Classic Clonalg
	$\omega = 10.667$	$\omega = 10.667$
1	0	0
2	0	36
3	0	48
4	0	36
5	0	36
6	0	0
7	144	84
8	0	48
9	0	0
10	0	36
11	0	36
12	0	36
13	0	0
14	0	36
15	0	36
16	96	96
17	96	96
18	84	84
19	72	72
20	0	0
21	72	72
Cost (\$)	38,637,600	49,240,000

**Table 19** | Performances of the modified Clonalg and the classic Clonalg for New York City network

Algorithm	$\omega$	Min. Cost (USD)	Max. Cost (USD)	Success rate in 20 runs (%)	Average Run Time (min)	Average Iteration Number
Modified	10.5088	36,660,000	37,764,900	85	14.7	780
	10.667	38,637,600	39,671,200	35	20.7	203
Classic	10.667	49,240,000	59,370,500	5	83.1	500

**Table 20** | Pressures at the nodes of New York network

Node	Pressures (ft)	
	$\omega = 10.5088$	$\omega = 10.667$
1	Reservoir	Reservoir
2	294.39	294.21
3	286.59	286.15
4	284.31	283.79
5	282.30	281.70
6	280.75	280.07
7	278.31	277.51
8	276.45	276.67
9	273.76	273.78
10	273.73	273.74
11	273.86	273.87
12	275.15	275.14
13	278.12	278.10
14	285.59	285.56
15	293.34	293.33
16	260.27	260.08
17	272.87	272.87
18	261.40	261.18
19	255.37	255.05
20	260.92	260.73

**Table 21** | Parameters of the modified Clonalg and the classic Clonalg for Go Yang network

Algorithm	$\omega$	$N_{Ab}$	$\beta$	$\rho$	Probability Rate	Max. Iteration
Modified	10.5088	50	1	2	0.01	100
	10.5879	50	1	2	0.01	100
	10.667	30	5	2	0.01	100
Classic	10.667	30	5	2	–	100

the analyses. Optimal costs obtained by the modified Clonalg are 419,000 USD (using  $\omega = 10.4973$ ,  $\omega = 10.5088$ ,  $\omega = 10.667$ ), 6,016,520 and 6,081,087 USD (using  $\omega = 10.5088$ ,  $\omega = 10.667$ , respectively), 36,660,000 and 38,637,600 USD (using  $\omega = 10.5088$ ,  $\omega = 10.667$ , respectively), 176,958,824, 176,994,561 and 177,009,557

won (using  $\omega = 10.5088$ ,  $\omega = 10.5879$ ,  $\omega = 10.667$ , respectively) for Two-loop, Hanoi, New York City and Go Yang, respectively. On the other hand, optimal costs for these networks in the related literature are 419,000 USD (Savic & Walters 1997; Keedwell & Khu 2005; Geem 2006), 6,056,000 USD (Vairavamoorthy & Ali 2000; Wu &

**Table 22** | Comparison of the results for Go Yang network

Pipe	Modified Clonalg (This study)			DE Dong <i>et al.</i> (2012)	GA Dong <i>et al.</i> (2012)	HS Geem (2006)	NLP Kim <i>et al.</i> (1994)
	$\omega = 10.5088$	$\omega = 10.5879$	$\omega = 10.667$	$\omega = 10.667$	$\omega = 10.667$	$\omega = 10.5879$	
1	200	150	150	N/A	N/A	150	200
2	125	150	150	N/A	N/A	150	200
3	100	125	125	N/A	N/A	125	125
4	100	150	125	N/A	N/A	150	125
5	80	100	100	N/A	N/A	100	100
6	100	100	80	N/A	N/A	100	100
7	80	80	80	N/A	N/A	80	80
8	80	80	80	N/A	N/A	100	80
9	80	80	80	N/A	N/A	80	80
10	80	80	80	N/A	N/A	80	80
11	80	80	80	N/A	N/A	80	80
12	80	80	80	N/A	N/A	80	80
13	80	80	80	N/A	N/A	80	80
14	80	80	80	N/A	N/A	80	80
15	80	80	80	N/A	N/A	80	80
16	80	80	80	N/A	N/A	80	80
17	80	80	80	N/A	N/A	80	80
18	80	80	80	N/A	N/A	80	100
19	80	80	80	N/A	N/A	80	125
20	80	80	80	N/A	N/A	80	80
21	80	80	80	N/A	N/A	80	80
22	80	80	80	N/A	N/A	80	80
23	80	80	100	N/A	N/A	80	80
24	80	80	80	N/A	N/A	80	80
25	80	80	80	N/A	N/A	80	80
26	80	80	80	N/A	N/A	80	80
27	80	80	100	N/A	N/A	80	80
28	80	80	80	N/A	N/A	80	80
29	80	80	80	N/A	N/A	80	100
30	80	80	80	N/A	N/A	80	80
Cost(won)	176,958,824	176,994,561	177,009,557	177,010,000	177,061,000	177,135,800	179,142,700

**Table 23** | Comparison of the modified Clonalg and the classic Clonalg for Go Yang network

Pipe	Modified Clonalg	Classic Clonalg
	$\omega = 10.667$	$\omega = 10.667$
1	150	150
2	150	150
3	125	125
4	125	125
5	100	100
6	80	80
7	80	80
8	80	80
9	80	80
10	80	80
11	80	80
12	80	80
13	80	80
14	80	80
15	80	80
16	80	80
17	80	80
18	80	80
19	80	80
20	80	80
21	80	80
22	80	80
23	100	100
24	80	80
25	80	80
26	80	80
27	100	100
28	80	80
29	80	80
30	80	80
Cost (won)	177,009,557	177,009,557

Walski 2005; Geem 2006), 36,660,000 USD (Geem 2006), and 177,010,000 won (Dong *et al.* 2012), respectively. In addition, optimal costs obtained by the classic Clonalg for these networks are 419,000 USD (using  $\omega = 10.667$ ), 6,085,284 USD (using  $\omega = 10.667$ ), 49,240,000 USD (using  $\omega = 10.667$ ), and 177,009,557 won (using  $\omega = 10.667$ ), respectively. Parameters of the modified Clonalg and the classic Clonalg, comparisons of the results, pressures at the nodes, and performances of the modified Clonalg and the classic Clonalg for all the networks are given in Tables 6–25.

## CONCLUSIONS

The value of  $\omega$  has a significant impact on the cost designs of the WDNs. In order to compare the modified Clonalg and the other algorithms (HS, GA, NLP, IA, SCE, and DE) in the related literature, the same values of  $\omega$  (10.4973, 10.5088 and 10.5879) were applied for the analyses in addition to EPANET v.2.0's  $\omega$  value of 10.667. Results showed that the modified Clonalg could find lower costs than the other algorithms with the same values of  $\omega$ , and appeared to be significantly successful and feasible for the cost designs of the WDNs.

In the application of the Two-loop network, the modified Clonalg obtained a higher success rate and a lower maximum cost (worst cost) than the classic Clonalg, although both algorithms could find the same minimum cost (419,000 USD). In the application of the Hanoi network, the modified Clonalg could find both a lower minimum cost with a higher success rate and a lower maximum cost than the classic Clonalg. In the application of the New York City network, the modified Clonalg could find both a lower minimum cost with a higher success rate and a lower maximum cost than the classic Clonalg. In the application of the Go Yang

**Table 24** | Performances of the modified Clonalg and the classic Clonalg for Go Yang network

Algorithm	$\omega$	Min. Cost (won)	Max. Cost (won)	Success rate in 20 runs (%)	Average Run Time (min)	Average Iteration Number
Modified	10.5088	176,958,824	176,994,561	90	3.9	17
	10.5879	176,994,561	177,010,359	25	4.0	17
	10.667	177,009,557	177,010,359	15	7.2	14
Classic	10.667	177,009,557	177,104,733	15	0.9	17

**Table 25** | Pressures at the nodes of Go Yang network

Node	Pressures (m)		
	$\omega = 10.5088$	$\omega = 10.5879$	$\omega = 10.667$
1	Reservoir	Reservoir	Reservoir
2	28.93	24.99	24.95
3	28.86	26.30	26.25
4	25.39	24.07	24.02
5	23.07	22.75	22.37
6	20.40	20.66	20.57
7	27.42	25.20	25.14
8	25.76	24.35	24.29
9	20.14	19.98	19.90
10	15.23	15.42	15.07
11	15.02	15.05	15.04
12	17.93	18.16	17.79
13	17.16	17.38	17.15
14	15.09	15.30	15.00
15	15.25	15.46	15.14
16	28.32	25.69	25.63
17	26.59	23.85	23.79
18	26.23	23.56	23.50
19	27.21	24.35	24.28
20	26.61	23.42	23.36
21	19.71	16.09	16.03
22	19.30	15.88	15.81

Network, the modified Clonalg and the classic Clonalg could find the same minimum cost (177,009,557 won) with the same success rate. But the modified Clonalg obtained a lower maximum cost than the classic Clonalg. All of these demonstrate that the modification in the mutation process increases the diversity (search capability) and improves the performance of the algorithm.

The modified Clonalg uses Equation (4) instead of Equation (2) for the cloning (the classic Clonalg uses Equation (2)). Equation (4) increases the running time in comparison with Equation (2) since more clones are generated by it. Therefore, the modified Clonalg took a longer time than the classic Clonalg in the analyses (the application of the New York City network is excepted since higher values of  $N_{Ab}$  and  $\beta$  for the classic Clonalg were assigned than for the modified Clonalg).

In future studies, performance of this model needs to be explored under various restrictions such as a velocity, maximum pressure in the node, variation in water demands depending on time, in addition to the minimum pressure requirements for the WDNs.

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## REFERENCES

- Alperovits, E. & Shamir, U. 1977 [Design of optimal water distribution systems](#). *Water Resources Research* **13**, 885–900.
- Bezerra, G. B., De Castro, L. N. & Von Zuben, F. J. 2004 A hierarchical immune network applied to gene expression data. In: *Third International Conference* (G. Nicosia, V. Cutello, P. J. Bentley & J. I. Timmis, eds). ICARIS, Catania, Sicily, Italy, Springer, Berlin, Heidelberg, pp. 14–27.
- Bhave, P. R. & Sonak, V. V. 1992 [A critical study of the linear programming gradient method for optimal design of water supply networks](#). *Water Resources Research* **28**, 1577–1584.
- Chu, C. W., Lin, M. D., Liu, G. F. & Sung, Y. H. 2008 [Application of immune algorithms on solving minimum-cost problem of water distribution network](#). *Mathematical and Computer Modelling* **48**, 1888–1900.
- Cunha, M. D. C. & Sousa, J. 1999 [Water distribution network design optimization: simulated annealing approach](#). *Journal of Water Resources Planning Management-ASCE* **125**, 215–221.
- Cunha, M. D. C. & Ribeiro, L. 2004 [Tabu search algorithms for water network optimization](#). *European Journal of Operational Research* **157**, 746–758.
- De Castro, L. N. & Von Zuben, F. J. 2000 [The Clonal Selection Algorithm with Engineering Applications](#). *GECCO'00-Workshop Proceeding*, pp. 36–37.
- De Castro, L. N. & Von Zuben, F. J. 2002 [Learning and optimization using the clonal selection principle](#). *IEEE Transactions on Evolutionary Computation* **6** (3), 239–251.
- De Castro, L. N. & Timmis, J. I. 2003 [Artificial immune systems as a novel soft computing paradigm](#). *Soft Computing* **7**, 526–544.
- Dong, X., Liu, S., Tao, T., Li, S. & Xin, K. 2012 [A Comparative study of differential evolution and genetic algorithms for optimizing the design of water distribution systems](#). *Journal of Zhejiang University-Science A (Applied Physics & Engineering)* **13**, 674–686.
- Eiger, G., Shamir, U. & Ben-Tal, A. 1994 [Optimal design of water distribution networks](#). *Water Resources Research* **30**, 2637–2646.



- Eusuff, M. 2004 Water Resources Decision Making Using Meta-Heuristic Optimization Methods, PhD Thesis, Department of Civil Engineering and Engineering Mechanics, University of Arizona, USA.
- Fujiwara, O. & Khang, D. B. 1990 A two-phase decomposition method for optimal design of looped water distribution networks. *Water Resources Research* **26**, 539–549.
- Fujiwara, O., Jenchaimahakoon, B. & Edirisinghe, N. C. P. 1987 Modified linear programming gradient method for optimal design of looped water distribution networks. *Water Resources Research* **23**, 977–982.
- Geem, Z. W. 2006 Optimal cost design of water distribution networks using harmony search. *Engineering Optimization* **38**, 259–277.
- Hajela, P., Yoo, J. & Lee, J. 1997 GA based simulation of immune networks applications in structural optimization. *Engineering Optimization* **29**, 131–149.
- Harmer, P. K., Williams, P. D., Gunsch, G. H. & Lamont, G. B. 2002 An artificial immune system architecture for computer security applications. *IEEE Transactions on Evolutionary Computation* **6**, 252–280.
- Keedwell, E. & Khu, S. T. 2005 A hybrid genetic algorithm for the design of water distribution networks. *Engineering and Applications Artificial Intelligence* **18**, 461–472.
- Kessler, A. & Shamir, U. 1989 Analysis of the linear programming gradient method for optimal design of water supply networks. *Water Resources Research* **25**, 1469–1480.
- Kim, J. H., Kim, T. G., Kim, J. H. & Yoon, Y. N. 1994 A study on the pipe network system design using non-linear programming. *Journal of Korean Water Resources Association* **27**, 59–67.
- Koster, M., Grauel, A., Klene, G. & Convey, H. 2003 A new paradigm of optimization by using artificial immune reactions. In: *Knowledge-Based Intelligent Information and Engineering Systems* (V. Palade, R. J. Howlett & L. C. Jain, eds). Springer, Berlin, Heidelberg, Oxford, UK, pp. 287–292.
- Lin, M. D., Liu, Y. H. & Chu, C. W. 2007 Scatter search heuristic for least-cost design of water distribution networks. *Engineering Optimization* **37**, 857–876.
- Liong, S. Y. & Atiquzzaman, M. 2004 Optimal design of water distribution network using shuffled complex evolution. *Journal of the Institution of Engineers* **44**, 93–107.
- Maier, H. R., Simpson, A. R., Zecchin, A. C., Foong, W. K., Phang, K. Y., Seah, H. Y. & Tan, C. L. 2003 Ant colony optimization for design of water distribution systems. *Journal of Water Resources Planning and Management-ASCE* **129**, 200–209.
- Montesinos, P., Garcia-Guzman, A. & Ayuso, J. L. 1999 Water distribution network optimization using a modified genetic algorithm. *Water Resources Research* **35**, 3467–3473.
- Reehuis, E. 2010 Multi-Objective Robust Optimization of Water Distribution Networks, Masters Thesis, Leiden Institute of Advanced Computer Science, Leiden University, The Netherlands.
- Rossman, L. 2000 EPANET 2 Users Manual, Technical Report EPA/600/R-00/057, Water Supply and Water Resources Division, National Risk Management Research Laboratory, U.S., Environmental Protection Agency, Cincinnati, OH.
- Savic, D. A. & Walters, G. A. 1997 Genetic algorithms for least-cost design of water distribution networks. *Journal of Water Resources Planning and Management ASCE* **123**, 67–77.
- Schaake, J. & Lai, D. 1969 Linear Programming and Dynamic Programming-Application of Water Distribution Network Design, Report 116, Hydrodynamics Laboratory, Department of Civil Engineering, Massachusetts Institute of Technology, Cambridge, Massachusetts.
- Simpson, A. R., Dandy, G. C. & Murphy, L. J. 1994 Genetic algorithms compared to other techniques for pipe optimization. *Journal of Water Resources Planning and Management-ASCE* **120**, 423–443.
- Tazawa, I., Koakutsu, S., Hirata, H. 1996 Immunity based genetic algorithm and its application to the VLSI floorplan design problem. In: *Proceedings of the IEEE Conference on Evolutionary Computation, Piscataway* (IEEE Neural Networks Council & K. J. S. Gakkai, eds). ICCC, IEEE, NJ, USA.
- Vairavamorthy, K. & Ali, M. 2000 Optimal design of water distribution systems using genetic algorithms. *Computer-Aided Civil and Infrastructure Engineering* **15**, 374–382.
- Van Dijk, M., Van Vuuren, S. J. & Van Zyl, J. E. 2008 Optimising water distribution systems using a weighted penalty in a genetic algorithm. *Water SA* **34**, 537–548.
- Varma, K. V. K., Shankar, N. & Bhallamudi, S. M. 1997 Optimal design of water distribution systems using an NLP method. *Journal of Environmental Engineering* **123**, 381–388.
- Wu, Z. Y. & Walski, T. 2005 Self-adaptive penalty approach compared with other constrain-handling techniques for pipeline optimization. *Journal of Water Resources Planning and Management* **131**, 181–192.
- Yates, D. F., Templeman, A. B. & Boffey, T. B. 1984 Computational complexity of the problem of determining least capital cost designs for water supply networks. *Engineering Optimization* **7**, 143–155.
- Zecchin, A. C., Simpson, A. R., Maier, H. R., Leonard, M., Roberts, A. J. & Berrisford, M. J. 2006 Application of two ant colony optimization algorithms to water distribution system optimization. *Mathematical & Computational Modelling* **44**, 451–468.

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