Water loss detection in water distribution networks by using modified Clonalg

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ABSTRACT

This study aims at the development of an optimization model based on a model calibration, using artificial immune systems (AIS) for quantifying and locating water loss in water distribution networks (WDNs) without using observed pressure data as used by previous studies in the related literature. The modified Clonal Selection Algorithm (modified Clonalg), a class of AIS, was used as a heuristic optimization technique in the model. EPANET 2, a widely known WDN simulator, was used in conjunction with the model. The model was applied to four-loop and six-loop virtual WDNs under steady-state conditions in order to test its performance in water loss detection in both pipes and nodes. Also, sensitivity analysis of the modified Clonalg was performed according to mutation coefficient to test its search capability in this optimization problem. The results showed that the model appeared to be promising in terms of water loss detection in WDNs.

Key words | artificial immune systems, leakage, model calibration, optimization, water distribution network, water loss detection

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INTRODUCTION

Water is of vital importance for all living creatures because it is a life source. This also increases the economic value of water. In this regard, the water loss detection comes to prominence to prevent water loss in water distribution networks (WDNs). Water loss in the WDNs occurs due to unauthorized water consumptions, meter inaccuracies, and leakages or bursts in pipes and nodes. Misiunas (2003) and De Silva *et al.* (2011) devised the most commonly used leakage detection techniques in WDNs, which are Static Mass Balance (Mounce *et al.* 2003), State Estimation (Andersen & Powell 2000), Transient Analysis (Covas *et al.* 2004; Savic *et al.* 2005), Acoustic Methods (Tafuri 2000). Within these techniques, various sensors, meters, monitoring systems and measurements (flow rate, pressure and temperature sensors detecting quasi-static signals, acoustic sensors detecting sound waves/noises, electromagnetic sensors using Faraday's law of induction, infrared thermography, transmitters emitting radio frequencies, manometers, ultrasonic flow meters utilizing propagation time of the ultrasonic signals, SCADA, tracing substances, etc.) are used and installed into WDNs. Therefore, the water loss detection is an expensive and difficult task. In order to facilitate the task, the optimization model was developed in this study based on a model calibration, using modified Clonal Selection Algorithm (modified Clonalg), a class of artificial immune systems (AIS). There are many studies such as Vitkovsky *et al.* (2000), Tabesh *et al.* (2009), Prasad (2010), Nasirian *et al.* (2013), Kang & Lansey (2014), Ribeiro *et al.* (2015), and Sanz *et al.* (2015) regarding water loss detection in WDNs based on a model calibration in the related literature. In these studies, many observed flow rates and pressure measurements in the field were used to detect water loss at some WDN points. The success of water loss detection of WDNs depends on the number of field measurements

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(flow rate and pressure). More field measurements facilitate the detection of greater water loss. But this increases the cost of the task due to lack of equipment. Thus, herein, the most important aim is to detect the maximum amount of water loss by using the minimum required field measurements. Within this aim, in this study, the model does not need to observe pressures in the field, and it uses observed flow rates in the initial points of pipes (not measured throughout pipes) and observed nodal demands in WDN nodes for detecting water loss including leakages in all pipes and unauthorized water consumptions in all nodes. Although there are many unknown leakages in WDN pipes which cannot be calculated by the continuity equation with the observed data, the model can detect locations and amounts of water loss. This demonstrates that the model minimizes the number of required field measurements used in a model calibration (pressures are not used) for detecting water loss in all pipes and WDN nodes. In order to test a search capability of the modified Clonalg in this optimization problem, the sensitivity analysis was carried out according to mutation coefficient. The model was applied to four-loop and six-loop virtual WDNs under steady-state conditions in order to test its performance in water loss detection. The results showed that the model can detect both locations and amounts of water loss in all pipes and of WDN nodes.

MATERIALS AND METHODS

Model formulation

Model calibration is the process of minimizing the discrepancy between the model predictions and field observations of pressures and flows to determine the physical and operational characteristics of an existing system. These characteristics include model parameters such as pipe roughness, nodal demand, operation status of pipes, pumps, valves and tanks (De Schaetzen *et al.* 2000; Walski 2001; Wu *et al.* 2002; Savic *et al.* 2009). Wu *et al.* (2002) defined model calibration as an implicit nonlinear optimization problem and used it for determining roughness coefficients of pipes via genetic algorithm (GA). Model calibration is also utilized for detecting water loss or leaks in WDNs. Wu & Sage (2006) presented an optimization-based approach using GA for quantifying and locating water loss via the process of hydraulic model calibration. Prasad (2010) proposed a model using Clonalg (De Castro & Von Zuben 2002) to determine model parameters including nodal demands, pipe roughness values, valve closures, pump controls and valve settings. Nasirian *et al.* (2013) studied leakage detection based on calibration in WDNs and introduced a novel optimization method with GA to calculate calibration and detect leakage within networks. In order to obtain model parameters in WDNs, an objective function used in the model calibration process is optimized by minimizing the discrepancy between the model predicted and the field observed values of junction pressures and pipe flows under boundary conditions such as tank levels, control valve setting and pump speeds. The objective function (f) was defined as follows (Wu *et al.* 2002):

$$\text{minimize} \quad \frac{\sum_{nh=1}^{NH} w_{nh}\left(\frac{H\text{sim}_{nh}-H\text{obs}_{nh}}{H\text{pnt}}\right)^2 + \sum_{nf=1}^{NF} w_{nf}\left(\frac{F\text{sim}_{nf}-F\text{obs}_{nf}}{F\text{pnt}}\right)^2}{NH+NF} \tag{1}$$

where $H\text{obs}_{nh}$ is the nh-th observed hydraulic grade (pressure), $H\text{sim}_{nh}$ is the nh-th model simulated hydraulic grade, $F\text{obs}_{nf}$ is the nf-th observed flow rate, $F\text{sim}_{nf}$ is the nf-th simulated flow rate, $H\text{pnt}$ is the hydraulic head per fitness point while $F\text{pnt}$ is the flow per fitness point, NH is the number of observed hydraulic grades and NF is the number of observed pipe flows, w_{nh} and w_{nf} are the weighting factors. Instead of Equation (1), Equation (2) was derived in this study so that pressures in the field need not be observed for water loss detection in WDNs:

$$\text{minimize} \quad \frac{\sum_{nd=1}^{ND}(D\text{sim}_{nd}-D\text{obs}_{nd})^2+\sum_{nf=1}^{NF}(F\text{sim}_{nf}-F\text{obs}_{nf})^2}{ND+NF} \tag{2}$$

where $D\text{obs}_{nd}$ is the nd-th observed junction (nodal) demand, $D\text{sim}_{nd}$ is the nd-th model simulated junction demand. In water loss detection, the objective function was minimized by considering the following constraints.

For each node, the continuity equation should be satisfied:

$$\sum Q_{\text{in}} - \sum Q_{\text{out}} = Q_e \tag{3}$$

where Q_{in} and Q_{out} are the inflow and outflow rate of the node, respectively, Q_e is the external inflow rate or demand at the node. For each node, the minimum pressure required is expressed as follows:

$$H_j \geq H_j^{\min} \quad j = 1, \ \ldots, \ M \tag{4}$$

where H_j is the pressure head at node j, $H_j^{\min}$ is the minimum required pressure head at node j, M is the number of nodes in WDN. The penalty function is also described in addition to the objective function (f) in case of violating the constraints. The penalty function is as follows:

$$\text{If } H_j < H_j^{\min} \rightarrow |H_j| + f \quad j = 1, \ \ldots, \ M \tag{5}$$

In this study, $H_j^{\min}$ was zero so that negative pressures do not occur in the nodes. The modified Clonalg developed by Eryigit (2015), a class of AIS, was used for minimizing the objective function. The modified Clonalg is illustrated in Figure 1 for optimization problems, where Ab is an antibody set (population) randomly constituted, f is an antibody's antigenic affinity corresponding to the objective function for a given antibody, C is a set of antibodies cloned, C^* is a set of matured (mutated) antibodies after the cloning process. In the modified Clonalg, new genes are generated for each clone with a certain probability depending on a given problem, called 'probability rate'. The number of clones generated for all antibodies can be calculated as follows (De Castro & Von Zuben 2002):

$$N_C = \sum_{i=1}^{N_{Ab}} \text{round}\,(\beta \cdot N_{Ab}) \quad i = 1, \ldots, N_{Ab} \tag{6}$$

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

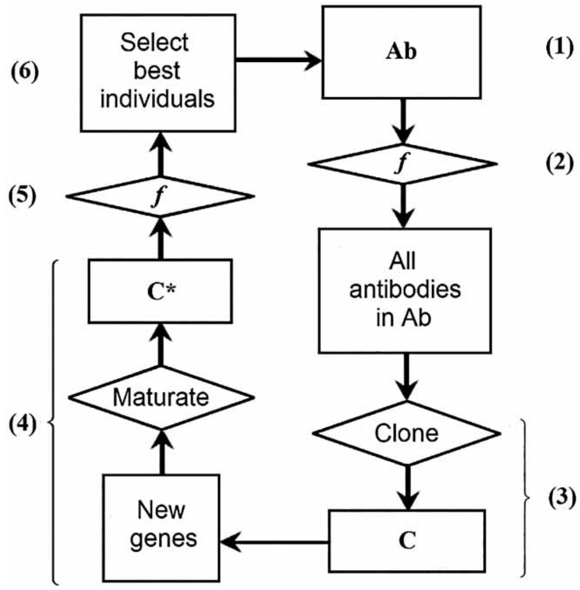

Figure 1 | Flow chart of the modified Clonalg for the optimization.

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

$$\alpha_i = \exp\,(-\rho \cdot f_i) \tag{7}$$

where α_i is the mutation rate for the clones exposed to the maturation process, ρ is a decay coefficient, and f_i is the affinity value (objective function value) normalized over the interval [0,1].

Description of Ab:

$$\overbrace{\begin{bmatrix} Ab_1 = x_{11} & \cdots & x_{1j} & \cdots & x_{1nd} \\ \vdots \quad \vdots & & & & \vdots \\ Ab_i = x_{i1} & & \ddots & & x_{ind} \\ \vdots \quad \vdots & & & & \vdots \\ Ab_{N_{Ab}} = x_{N_{Ab}1} & \cdots & x_{N_{Ab}j} & \cdots & x_{N_{Ab}nd} \end{bmatrix}} \rightarrow \overbrace{\begin{bmatrix} f_1 \\ \vdots \\ f_i \\ \vdots \\ f_{N_{Ab}} \end{bmatrix}}^{f} \tag{8}$$
$$i = 1, \ \ldots, N_{Ab} \quad j = 1, \ \ldots, \ nd$$

where N_{Ab} is the total number of antibodies in Ab, x_{ij} is the gene of Ab_i, corresponding to a decision variable of the objective function, nd is the number of genes (decision variables) of Ab_i. In this study, x_{ij} corresponds to nodal water demand. Unauthorized water consumption in

Table 1 | Node and pipe data of four-loop WDN

Node	Elevation (m)	Base demand (l/s)	Pipe	Length (m)	Diameter (mm)	C_p
Reservoir	75	–	1	500	400	100
1	0	50	2	500	400	100
2	0	40	3	500	300	100
3	0	40	4	500	300	100
4	0	50	5	500	300	100
5	0	40	6	500	200	100
6	0	30	7	500	200	100
7	0	40	8	500	300	100
8	0	35	9	500	200	100
9	0	40	10	500	200	100
			11	500	200	100
			12	500	200	100
			13	1,000	600	100

Table 2 | Operating data of four-loop WDN

Node	Observed demand (l/s)	Water loss in node (l/s)	Pipe	*Observed flow rate (l/s)	Leakage in pipe (l/s)
Reservoir	–	–	1	198.33	5
1	56	6	2	195.67	5
2	44	4	3	68.7	3
3	43	3	4	67.55	4
4	57	7	5	78.98	3
5	45	5	6	30.98	0
6	36	6	7	35.75	4
7	46	6	8	81.78	5
8	38	3	9	30.78	0
9	43	3	10	36.49	4
			11	25.27	4
			12	26.73	5
			13	450	–

*All observed flow rates were assumed to be measured only at initial points of pipes in WDNs.
Although there are no leakages in pipes 6 and 9, they were assumed as pseudo nodes (nodes 14 and 20) due to their being leak candidates.

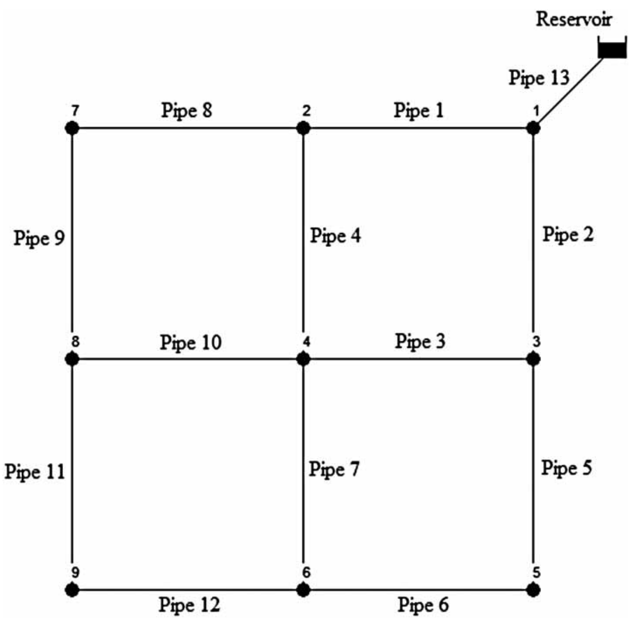

Figure 2 | Layout of four-loop WDN.

nodes and leakages in pipes was considered as water loss in WDNs. All leakages in pipes were assumed as a pseudo node and simulated as a demand (Poulakis *et al.* 2003). Unauthorized consumptions were added as a demand by demand multipliers to base demands in actual nodes (Wu & Sage 2006). This operation was formulated as follows:

$$\left.\begin{array}{l} AD_j = BD_j + \text{rand} \cdot BD_j \\ UC_j = AD_j - BD_j \end{array}\right\} \quad j = 1, \ \ldots, \ N_{AN} \tag{9}$$

where AD_j is an actual demand in node j, BD_j is a base demand in node j, UC_j is an unauthorized consumption in node j, rand generates a random number in the interval [0–1], N_{AN} is the number of actual nodes in WDNs. These actual demands obtained by the model were used as Dsim in Equation (2). Leakages in pipes are represented as follows:

$$L_j = L_{\min} + \text{rand} \cdot (L_{\max} - L_{\min}) \quad j = 1, \quad \ldots, \quad N_{PN} \tag{10}$$

where L_j is a leakage in pseudo node j, $L_{\min}$ is a lower limit, $L_{\max}$ is a upper limit, N_{PN} is the number of pseudo nodes assumed in WDNs. Herein, the interval between $L_{\min}$ and $L_{\max}$ was 0 [total amount of water loss]. Total amount of water loss equals the difference between observed total Q_{in} from the reservoir into the WDN and total of base demands. Nodal demands in actual and pseudo nodes (AD and L) are genes (x) of Ab_i (see Equation (8)), and the objective function (Equation (2)) was minimized depending on the genes formed and mutated through the processes of the modified Clonalg. EPANET 2, a widely known WDN simulator, was used for hydraulic computations (Rossman 2000). The optimization model was run 20 times for four-loop and six-loop WDNs until reaching the maximum iteration number in each run. Random seed (random number generation) was applied while constituting the initial set in each run. In the study, a PC with Intel I5 Core 2.5 GHz (3.1 GHz with Turbo Boost) and Matlab 2012a programming were used for the analyses. Note that while solving the hydraulic calculations in each iteration, flow rates obtained by the model are used as F sim in Equation (2), and the distribution of obtained flow rates in the WDNs depends on the decision variables (AD and L).

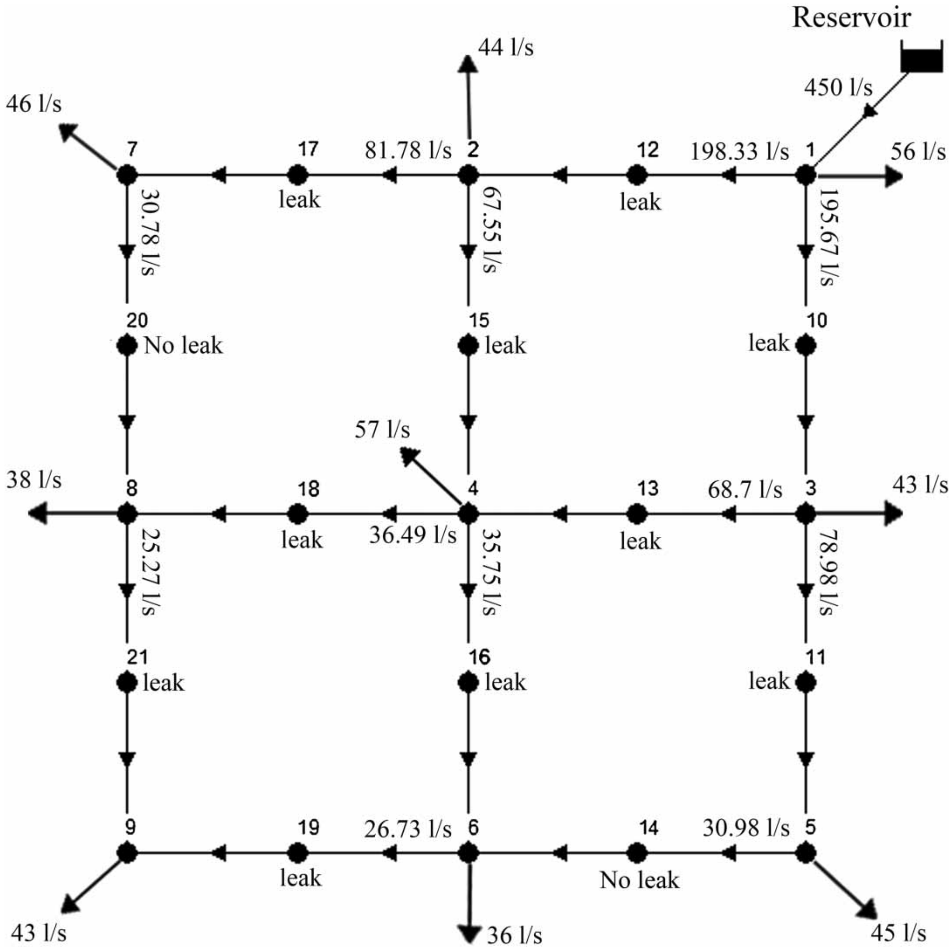

Figure 3 | Operating layout of four-loop WDN.

Table 3 | Node and pipe data of six-loop WDN

Node	Elevation (m)	Base demand (l/s)	Pipe	Length (m)	Diameter (mm)	C_p
Reservoir	75	–	1	500	500	100
1	0	50	2	500	500	100
2	0	45	3	500	300	100
3	0	40	4	500	300	100
4	0	35	5	500	300	100
5	0	50	6	500	200	100
6	0	60	7	500	300	100
7	0	55	8	500	400	100
8	0	40	9	500	250	100
9	0	55	10	500	200	100
10	0	60	11	500	150	100
11	0	55	12	500	250	100
12	0	50	13	500	200	100
			14	500	150	100
			15	500	200	100
			16	500	150	100
			17	500	200	100
			18	1,000	750	100

Table 4 | Operating data of six-loop WDN

Node	Observed demand (l/s)	Water loss in node (l/s)	Pipe	*Observed flow rate (l/s)	Leakage in pipe (l/s)
Reservoir	–	–	1	348.51	3
1	55	5	2	282.49	0
2	47	2	3	120.21	3
3	42	2	4	107.8	4
4	36	1	5	106.29	4
5	56	6	6	44.29	3
6	65	5	7	111.58	2
7	61	6	8	190.7	2
8	44	4	9	90.23	5
9	58	3	10	44.43	0
10	63	3	11	20.46	2
11	58	3	12	87.87	5
12	54	4	13	56.47	0
			14	20.47	5
			15	48.2	1
			16	18.67	5
			17	43.33	3
			18	686	–

*All observed flow rates were assumed to be measured only at initial points of pipes in the WDN.
Although there are no leakages in pipes 2, 10 and 13, they were assumed as pseudo nodes (nodes 13, 21 and 25) due to their being leak candidates.

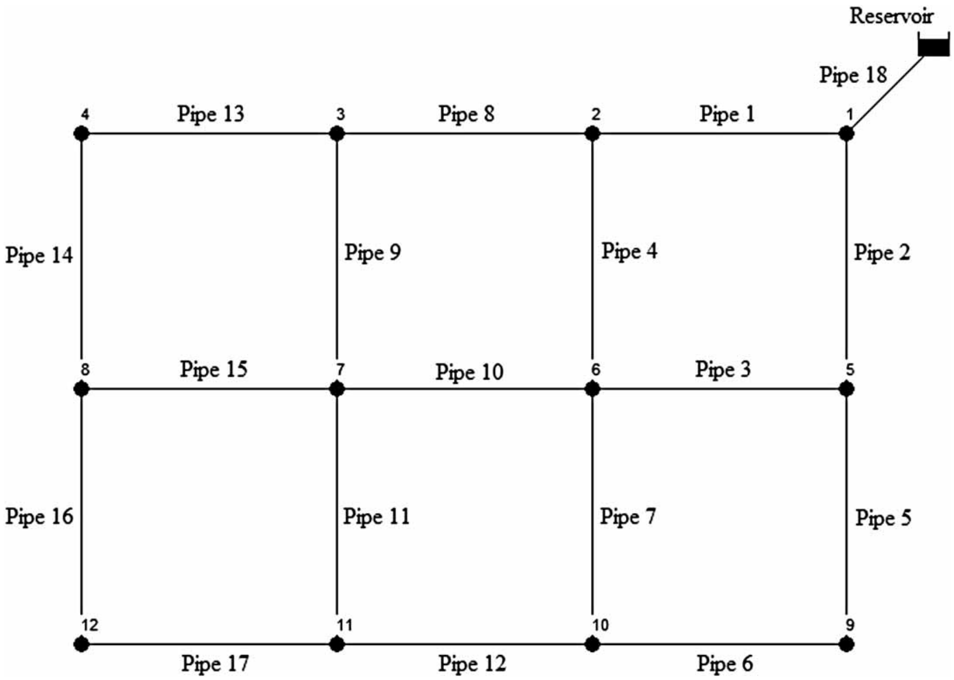

Figure 4 | Layout of six-loop WDN.

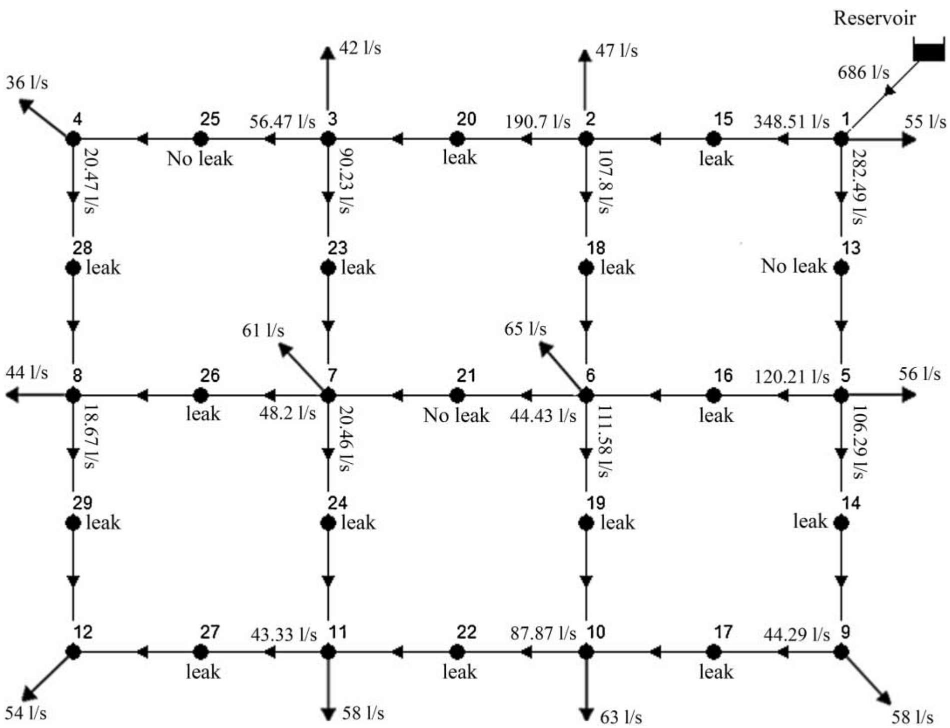

Figure 5 | Operating layout of six-loop WDN.

Four-loop WDN scenario

This network consists of 10 actual nodes including nodes 1–9, and a reservoir, 13 pipes with four loops, and is fed by the gravity from a reservoir with a 75 m fixed head. Pipe roughness coefficient (C_p) was 100 in all pipes. Nodes 10–21 are pseudo nodes representing leakages in pipes. Also, unauthorized water consumption was added to base demands in nodes 1–9 as water loss. In this WDN, total amount of water loss is 85 l/s ($L_{\max}$) (total inflow of 450 l/s – total base demands of 365 l/s). Node and pipe data, operating data, and the layouts of four-loop WDN are shown in Tables 1 and 2, Figures 2 and 3, respectively. As seen in Figure 3, leakages in pipes 1, 2, 5, and 8 (pseudo nodes 12, 10, 11, and 17, respectively) can be calculated by Equation (3) with the observed data (e.g., pseudo node $12 = 198.33$ l/s – (44 l/s + 81.78 l/s + 67.55 l/s)) while leakage in pipes 3, 4, 6, 7, 9, 10, 11 and 12 (pseudo nodes 13, 15, 14, 16, 20, 18, 21 and 19, respectively) cannot be calculated because the flows are not measured throughout pipes.

Six-loop WDN scenario

This network consists of 13 actual nodes including nodes 1–12, and a reservoir, 18 pipes with six loops, and is fed by the gravity from a reservoir with a 75 m fixed head. Pipe roughness coefficient (C_p) was 100 in all pipes. Nodes 13–29 are pseudo nodes representing leakages in pipes. Also, unauthorized water consumption was added to base demands in nodes 1–12 as water loss. In this WDN, total amount of water loss is 91 l/s ($L_{\max}$) (total inflow of 686 l/s – total base demands of 595 l/s). Node and pipe data, operating data, and the layouts of six-loop WDN are shown in Tables 3 and 4, Figures 4 and 5, respectively. As it is seen in Figure 5, leakages in pipes 1, 2, 5, 8, and 13 (pseudo nodes 15, 13,

Table 5 | Parameters and performances of the modified Clonalg used for the optimization

WDN	N_{Ab}	β	ρ	Probability rate	Iteration number	Min. f (l/s)	Max. f (l/s)	*Mean f (l/s)	*Mean run time (min)
Four-loop	30	1	8	0.1	20,000	1.02×10^{-4}	2.14×10^{-4}	$1.52 \times 10^{-4} \pm 3.3 \times 10^{-5}$	186.7 ± 4.1
Six-loop	30	1	8	0.1	20,000	5.2×10^{-4}	20.3×10^{-4}	$13.9 \times 10^{-4} \pm 4.2 \times 10^{-4}$	256.4 ± 6.9
	30	1	9	0.1	20,000	2.36×10^{-4}	20.7×10^{-4}	$8.99 \times 10^{-4} \pm 5.1 \times 10^{-4}$	253.5 ± 0.4
	30	1	10	0.1	20,000	3.29×10^{-4}	19.5×10^{-4}	$8.64 \times 10^{-4} \pm 5.1 \times 10^{-4}$	258.9 ± 13.7

N_{Ab}: Number of population *Ab*. β: Multiplying coefficient for the cloning. ρ: Decay coefficient.
*Average of 20 runs.

Table 6 | Comparison of mean predicted and actual water loss (leakages and unauthorized consumption) in nodes and pipes of four-loop WDN

Node	*Mean predicted demand (l/s)	Observed demand (l/s)	*Mean pressure (m)	Pipe	*Mean predicted leakage (l/s)	Leakage (l/s)
1	56.000 ± 0.004	56	69.21 ± 0.000	1	5.001 ± 0.028	5
2	44.000 ± 0.008	44	64.75 ± 0.001	2	4.999 ± 0.031	5
3	43.001 ± 0.007	43	64.86 ± 0.001	3	3.015 ± 0.065	3
4	56.998 ± 0.004	57	62.36 ± 0.000	4	4.007 ± 0.056	4
5	45.005 ± 0.006	45	61.60 ± 0.001	5	2.974 ± 0.020	3
6	35.995 ± 0.007	36	57.31 ± 0.003	6	0.043 ± 0.023	0
7	46.003 ± 0.006	46	61.35 ± 0.001	7	3.975 ± 0.023	4
8	37.996 ± 0.007	38	57.10 ± 0.003	8	4.978 ± 0.011	5
9	43.000 ± 0.004	43	54.56 ± 0.001	9	0.047 ± 0.017	0
				10	3.971 ± 0.020	4
				11	3.994 ± 0.072	4
				12	4.996 ± 0.067	5

*Average of 20 runs.

Table 7 | Comparison of mean predicted and actual water loss (leakages and unauthorized consumption) in nodes and pipes of six-loop WDN

Node	*Mean predicted demand (l/s)			Observed demand (l/s)	*Mean pressure (m)			Pipe	*Mean predicted leakage (l/s)			Leakage (l/s)
	$\rho=8$	$\rho=9$	$\rho=10$		$\rho=8$	$\rho=9$	$\rho=10$		$\rho=8$	$\rho=9$	$\rho=10$	
1	54.995 ± 0.01	54.999 ± 0.00	54.998 ± 0.00	55	70.74 ± 0.00	70.74 ± 0.00	70.74 ± 0.00	1	2.989 ± 0.06	2.978 ± 0.03	2.986 ± 0.04	3
2	47.001 ± 0.02	47.003 ± 0.01	47.001 ± 0.01	47	66.39 ± 0.00	66.39 ± 0.00	66.39 ± 0.00	2	0.056 ± 0.03	0.040 ± 0.02	0.037 ± 0.02	0
3	41.991 ± 0.02	41.993 ± 0.01	41.994 ± 0.01	42	62.18 ± 0.00	62.18 ± 0.00	62.18 ± 0.00	3	2.934 ± 0.05	2.949 ± 0.03	2.952 ± 0.04	3
4	35.954 ± 0.02	35.958 ± 0.02	35.957 ± 0.02	36	49.15 ± 0.02	49.15 ± 0.02	49.15 ± 0.01	4	3.981 ± 0.06	4.001 ± 0.03	4.000 ± 0.03	4
5	55.988 ± 0.01	55.991 ± 0.01	55.992 ± 0.00	56	67.77 ± 0.00	67.77 ± 0.00	67.77 ± 0.00	5	3.984 ± 0.08	3.998 ± 0.05	3.987 ± 0.05	4
6	65.012 ± 0.01	65.006 ± 0.01	65.005 ± 0.01	65	60.59 ± 0.00	60.59 ± 0.00	60.59 ± 0.00	6	2.977 ± 0.14	2.980 ± 0.09	2.996 ± 0.09	3
7	61.006 ± 0.01	61.005 ± 0.01	61.005 ± 0.00	61	52.21 ± 0.01	52.21 ± 0.00	52.21 ± 0.00	7	2.047 ± 0.13	2.030 ± 0.09	2.021 ± 0.10	2
8	43.988 ± 0.02	43.986 ± 0.01	43.983 ± 0.01	44	42.68 ± 0.02	42.68 ± 0.02	42.68 ± 0.01	8	2.037 ± 0.09	2.025 ± 0.05	2.025 ± 0.06	2
9	58.003 ± 0.02	57.999 ± 0.01	58.002 ± 0.01	58	62.12 ± 0.00	62.12 ± 0.00	62.12 ± 0.00	9	4.882 ± 0.07	4.920 ± 0.06	4.917 ± 0.06	5
10	62.996 ± 0.01	62.998 ± 0.01	62.998 ± 0.01	63	54.30 ± 0.00	54.30 ± 0.00	54.30 ± 0.00	10	0.058 ± 0.04	0.029 ± 0.03	0.028 ± 0.03	0
11	58.006 ± 0.01	58.006 ± 0.01	58.004 ± 0.01	58	44.82 ± 0.01	44.82 ± 0.01	44.82 ± 0.00	11	2.076 ± 0.11	2.053 ± 0.06	2.059 ± 0.07	2
12	53.997 ± 0.01	53.997 ± 0.01	53.997 ± 0.01	54	37.33 ± 0.01	37.33 ± 0.01	37.33 ± 0.00	12	4.924 ± 0.08	4.938 ± 0.06	4.936 ± 0.06	5
								13	0.143 ± 0.06	0.128 ± 0.06	0.129 ± 0.06	0
								14	4.733 ± 0.11	4.781 ± 0.14	4.766 ± 0.10	5
								15	1.255 ± 0.13	1.220 ± 0.16	1.241 ± 0.11	1
								16	4.865 ± 0.17	4.864 ± 0.13	4.856 ± 0.10	5
								17	3.123 ± 0.17	3.127 ± 0.13	3.131 ± 0.10	3

*Average of 20 runs.

14, 20, and 25, respectively) can be calculated by Equation (3) with the observed data (e.g., pseudo node 15 = 348.51 l/s − (47 l/s + 190.7 l/s + 107.8 l/s)) while leakages in pipes 3, 4, 6, 7, 9, 10, 11, 12, 14, 15, 16, and 17 (pseudo nodes 16, 18, 17, 19, 23, 21, 24, 22, 28, 26, 29, and 27, respectively) cannot be calculated because the flows are not measured throughout pipes.

RESULTS AND DISCUSSION

The model minimizes the objective function (see Equation (2)) for detecting water loss (unauthorized water consumption in actual nodes and leakages in pipes) in WDNs, and the average of the best (minimum) objective function values after 20 runs is zero (see Table 5). As seen in Tables 6 and 7, leakages and water demands predicted by the model, and actual leakages and observed water demands are almost the same. Also, within hydraulic calculations, pressures in all actual nodes were obtained appropriately, and any negative pressure did not occur in nodes. In order to analyze the sensitivity of the model, ρ (decay coefficient), one of the most important parameters of the modified Clonalg, was selected because of playing a critical role in search capability in optimization problems. α (mutation rate) changes values of genes of all antibodies (AD and L) during the mutation process, and it is very sensitive to ρ. Therefore, parameter ρ affects the model calibration directly because AD and L are decision variables of the model calibration in this study. For 8, 9, and 10 values of ρ, the model was applied to six-loop WDN. The results demonstrated that the modified Clonalg used in the model shows a steady and stable performance for water loss detection in the WDN (see Table 7).

The model could detect both locations and amounts of water loss in all nodes and pipes of the WDNs without using observed pressure data (see Equation (1)). Also, although there are many unknown leakages in WDNs, which cannot be calculated by Equation (3) with the observed data, they were detected successfully. These demonstrate that the model minimizes the number of required field measurements used in a model calibration (pressures are not used) for detecting water loss in all pipes and nodes of WDNs. Moreover, the sensitivity analysis of the modified Clonalg was carried out according to ρ (decay coefficient) to test its search capability in the optimization problems. The results showed that the model appeared to be significantly successful and feasible for water loss detection in WDNs. In future studies, the performance of this model needs to be explored in different WDNs.

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