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# Selection of Real-Coded Genetic Algorithm parameters in solving simulation–optimization problems for the design of water distribution networks

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## ABSTRACT

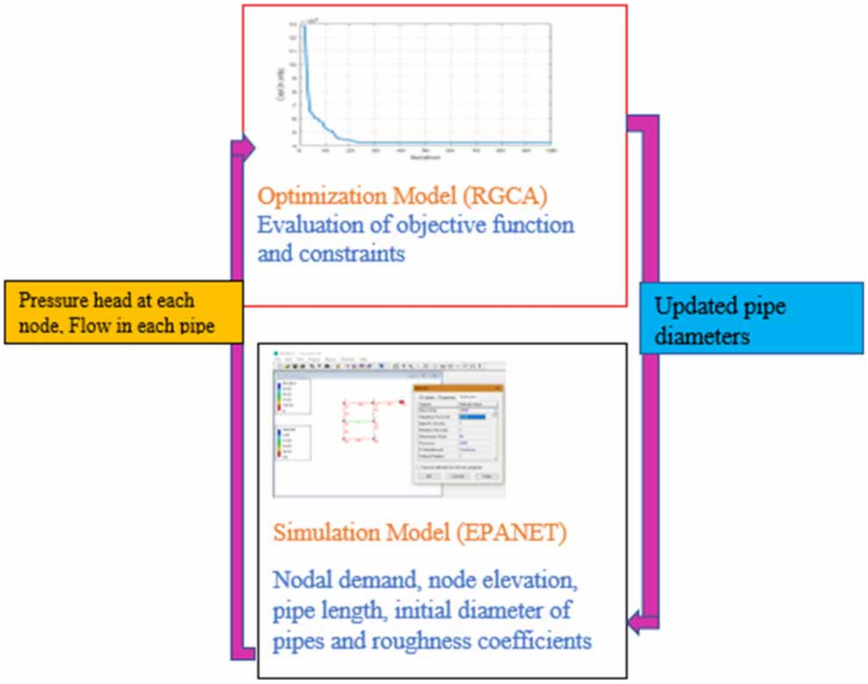
The design of the water distribution network (WDN) is very difficult mainly due to the nonlinear relation between head and flow. The distribution network should also be cost-effective. In any simulation–optimization approach, the computational time requirement is very high for very complex problems. The optimization module plays a crucial role in reducing the computational time. This study aims to apply a simulation–optimization approach to designing a WDN. EPANET is selected as the simulation model and Real-Coded Genetic Algorithm (RCGA) is selected as the optimization module. To link the simulation module with the optimization module, a program is written in MATLAB. The developed simulation–optimization approach was applied to two benchmark network problems to check the suitability of the method. The parameters of the RCGA were optimized for the two networks. The computational efficiency of the developed simulation–optimization model is checked based on the number of function evaluations. For both networks, the number of function evaluations to get the optimum network design was less than the number of function evaluations required for other methods mentioned in the literature.

**Key words:** Real-Coded Genetic Algorithm, simulation–optimization, water distribution system

## HIGHLIGHTS

- Simulation–optimization approach is adopted for the design of WDNs.
- Developed an interface in MATLAB to link simulation and optimization.
- EPANET is used as the simulation module and RCGA as the optimization module.
- The parameters of Real Coded Genetic Algorithm is optimized.
- The developed simulation optimization model is applied to two benchmark problems.

## GRAPHICAL ABSTRACT




## 1. INTRODUCTION

Proper design of water distribution networks (WDN) plays a very important role in distributing adequate quality and quantity of water to consumers (Kanakoudis 2004). Two types of simulation approaches are used to analyze WDNs, namely steady-state and extended-period simulation. In steady-state simulation, the flows and other attributes do not change over time; whereas, in the extended-period simulation, the variation of flows and other attributes are simulated over various time periods (Cesario 1995). The simulation of a WDN is a difficult process. The main task in the analysis of a WDN involves solving simultaneous nonlinear equations (Kessler & Shamir 1989; Eiger *et al.* 1994; Dandy *et al.* 1996) These equations include a continuity equation for every node, an energy equation, and the equation relating pipe flow and the head-losses. There are many useful and efficient computer programs available for WDN simulation. One of the most popular computer programs is EPANET (Rossman 1993). To determine the optimum parameters in a WDN, the traditional approach is to use the trial and error method by applying a simulation model. The trial and error approach is a cumbersome task because, for the determination of optimum parameters, it is necessary to adjust the variables based on the results from the simulation model until some pre-defined specifications are satisfied. The complexity of this process increases as the number of decision variables increases (Wu & Simpson 2001) One solution to these problems is to use simulation–optimization approach. The combined simulation–optimization application in a WDN is generally based on a surrogate method or direct linking of the simulation and optimization model. In the surrogate method (Broad *et al.* 2005, 2010), the response of the complex simulation model is captured by simple models like artificial neural networks (ANNs) and then these simple models will be linked with the optimization model. In direct linking of simulation–optimization approach for any application (Mohan *et al.* 2007; Batista do Egito *et al.* 2023), simulation models are directly linked with an optimization model.

Kessler & Shamir (1989) described that the nonlinear relationship between flow and head-loss and the existence of discrete variables, such as pipe market sizes, make the optimum network design exceedingly complex. The objective function is also nonlinear and non-convex. Many of the traditional optimization methods namely Linear Programming, Nonlinear Programming, and Dynamic Programming (Alperovits & Shamir 1977; Chiplunkar *et al.* 1986; Bhave 1988; Kessler & Shamir 1989; Lansey & Mays 1989; Eiger *et al.* 1994) cannot be used to determine the global optimum results of WDN problems. Nowadays, the global optimization techniques namely Genetic Algorithm (GA) (Goldberg 1989), Simulated Annealing (Cunha & Sousa (1999), Particle Swarm Optimization (PSO), and Ant Colony Optimization Algorithms are widely used for optimizing

WDN. Recently many researchers have adopted other metaheuristic algorithms namely Grass Hopper Optimization Algorithm, Sparrow Search Algorithm, and Artificial Bee Colony Algorithm to a few optimization problems (Chen *et al.* 2023; Wang *et al.* 2023; Yao *et al.* 2023). The most commonly used metaheuristic approach is genetic algorithms for a wide variety of problems (Goldberg 1989; Simpson *et al.* 1994; Savic & Walters 1997; Gupta *et al.* 1999; Wu & Simpson 2002; Pramada *et al.* 2018a, 2018b; Sangroula *et al.* 2022; Surono *et al.* 2022). Savic & Walters (1997) developed a GA program called GANET for the least-cost design of WDNs. In their study, the combined simulation–optimization problem of the least-cost design of WDNs was formulated and it was shown that GA was suitable for solving WDN problems. Vairavamoorthy & Ali 2000 proposed a methodology for the optimal design of WDNs using GA and used Pipe Index Vector for controlling the GA search.

Determining the best design for a WDN has always been very problematic for water resources managers. In any simulation–optimization approach, the computational time requirement for very complex problems is one of the biggest issues. High-performance computing facilities and parallel computing can significantly reduce the computational time for complex problems. Jetmarova *et al.* (2017) stated that even with efficient optimization algorithms or with high-performance computing or parallel computing, WDN designs are still not computationally efficient. In these cases, choosing an optimization module with less function evaluation will help to reduce the computational time. Function evaluation is the average number of objective function/fitness function evaluations until the stopping criterion has been reached within each run. Recently, population-based search algorithms have been extensively used in the field of WDN design. Even though Real-Coded Genetic Algorithm (RCGA) is very effective in handling various engineering problems, there are only limited studies related to the selection of parameters of RCGA to get the optimum design of the WDN. The main objective of the present study is the selection of parameters of RCGA in a simulation–optimization framework for getting the global optimal results of WDN with a smaller number of function evaluations.

## 2. MATERIALS AND METHODS

In this study, EPANET is used as the simulation module and RCGA as the optimization module.

### 2.1. Simulation model – EPANET

A WDN consists of various components namely pipes, nodes, pumps, valves, storage tanks or reservoirs, etc. EPANET is used as the simulation model in this study. EPANET is a computer program that performs an extended-period simulation of hydraulic and water quality behavior within pressurized pipe networks (Rossman 1993). It has functionalities for tracking the flow in each pipe, the nodal pressure, the elevation of water in each tank, and the transport of chemicals through the network during the simulation period.

### 2.2. Optimization model

The objective function comprises minimizing the total cost of the network which is the sum of the cost of the pipe of a particular diameter in the network. It is given as:

$$Min\ F(D_1, D_2, \ldots, D_n) = \sum_{i=1}^{n} c(D_i, L_i) \tag{1}$$

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

The cost comprises only of the pipe cost which varies with respect to the diameters of the networks in this study.

The constraints comprise the continuity equation at the nodes, the energy balance equation along a loop, and maintaining the minimum pressure head requirements at the node.

For every junction node other than the source, the continuity equation must be satisfied. The constraint is given as:

$$\sum Q_{in} - \sum Q_{out} = 0 \tag{2}$$

where $Q_{in}$ is the flow into the node, $Q_{out}$ is the flow out of the node.

For each loop, the total energy is conserved. This is given as:

$$\sum h_f - \sum E_p = 0 \tag{3}$$

where $E_p$ is the energy put into the liquid by pump, $h_f$ is the head-loss in a pipe using the Hazen–Williams formula.

The head constraints for each of the node is given as:

$$H_j \geq H_j^{min} \quad j = 1, 2, .., M \tag{4}$$

where $H_j$ is the head value of the node, $H_j^{min}$ is the minimum required head at the same node, $M$ is the total number of nodes in the network.

$$H_j \leq H_j^{max} \qquad j = 1, 2, .., M \tag{5}$$

where $H_j^{max}$ is the maximum head at the node.

The above optimization model is solved using RCGA. GA is a search technique based on the principles of natural selection. Holland developed the GA original theory in 1975. GAs, which fall under the domain of evolutionary algorithms, simulate the process of natural selection. In the domains of engineering and computer science, they are effective global optimization approaches that address challenging issues in engineering. In order to find more accurate approximations of a solution, a population of potential solutions is incorporated into the search space. At first, a large number of the population are generated at random. The objective function of these populations is then assessed. If the termination conditions are not satisfied after one generation, the process of choosing individuals based on their level of fitness in the feasible domain produces a new set of approximations. This technique produces improved children (offspring). There are a few parameters required to run a genetic algorithm, namely population size, the mutation probability, and the crossover probability. The usual way to get these parameters is to do a lot of experimentation to find a set of values that solves a particular problem. A broad rule of thumb, to start with, is to use a mutation probability of 0.05, a crossover rate of 0.6, and a population size of about 50. (Goldberg *et al.* 2005) RCGA was first implemented by Wright in 1991 (Wright 1991). RCGAs do not use any coding (eg. binary coding) of the problem variables; instead, they work directly with the variables. RCGA is simple and straightforward compared to binary-coded GA.

### 2.3. Interfacing program to link EPANET with optimization module

In the present study, EPANET is linked with the RCGA. An interfacing program is developed in MATLAB, which calls EPANET to check the performance of the network, and then the information from EPANET is passed to the optimization module to check whether the solution is optimum or not. The nodal demand, node elevation, pipe length, and roughness coefficients are given as input to the EPANET. The approximate pipe diameters are also given as an input to the simulation model. EPANET then solves the hydraulic equations and estimates the pressure head at the nodes and the pipe flows. The pressure head at the nodes and flows in each pipe resulting from EPANET model runs are then passed back to the optimization module (Figure 1). The information is fed from the optimization module to EPANET through the input file (.inp) of the simulation model.

The program is written in MATLAB (version 2019a) to link the simulation and optimization modules. After creating the pipe network in EPANET, the file needs to be saved in (.inp) format rather than (.net) to run in MATLAB. EPANET toolkit for MATLAB needs to be downloaded and installed. Figure 2 shows the methodology to link the simulation model with the optimization model.

## 3. RESULTS AND DISCUSSION

The developed methodology for the optimal design of a WDN is applied to two benchmark problems such as a Two-Loop WDN reported by Alperovits & Shamir (1977) and GoYang WDN reported by Kim *et al.* (1994), and its performance is evaluated by comparing the results with past literature.

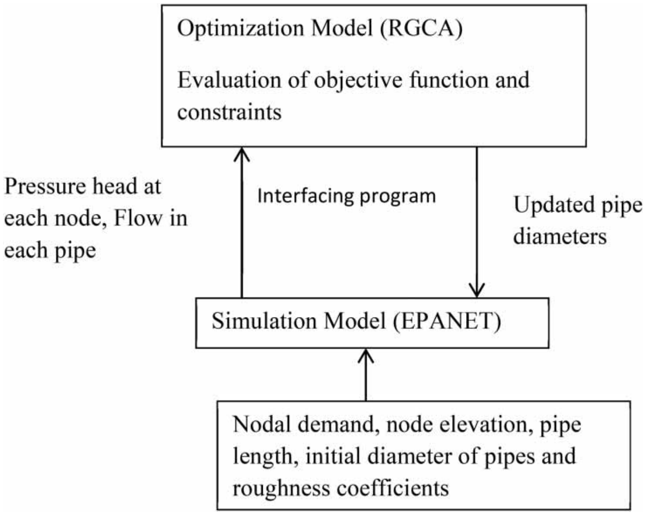



**Figure 1** | Linking optimization model and simulation model.

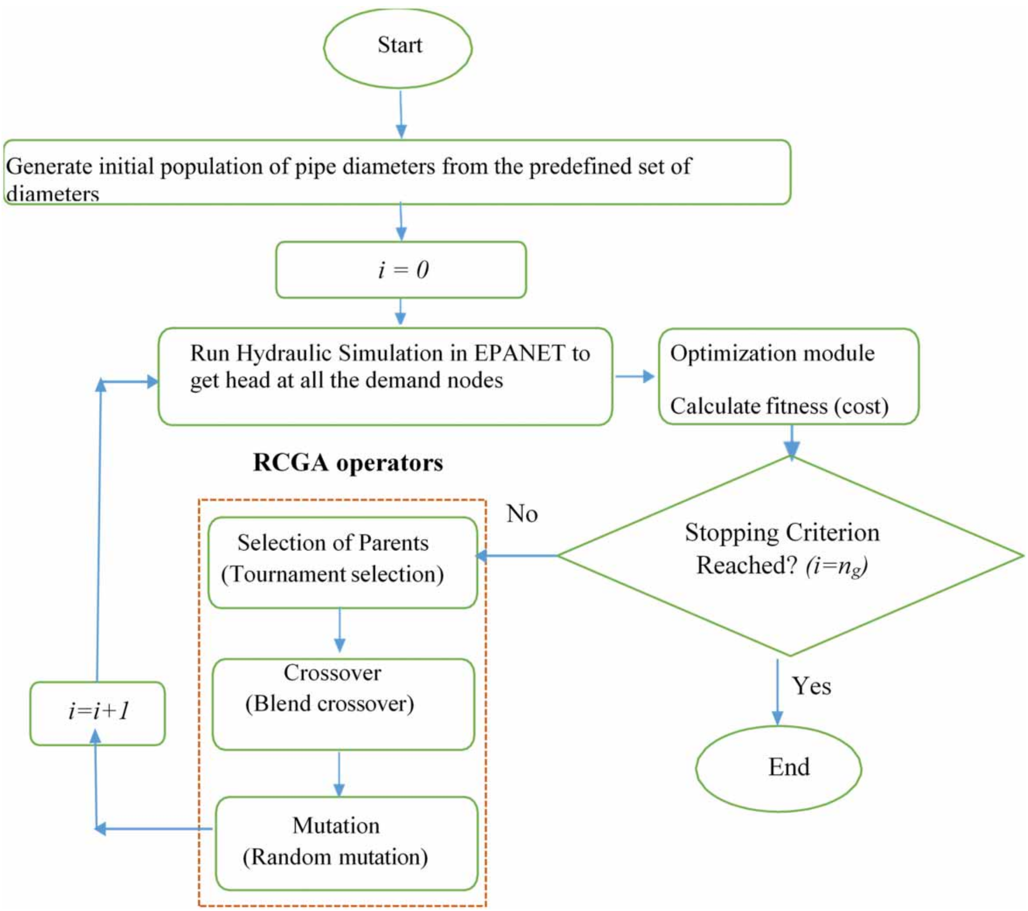



**Figure 2** | Steps in the simulation–optimization model for least-cost design of WDS using RCGA.

### 3.1. Benchmark problem 1 – Two-Loop WDN

Two-Loop WDN was first reported by Alperovits and Shamir as the least-cost design of WDN. Thereafter, many researchers used this network to test their approach. In this study, network configuration, with relevant network data, was taken from Alperovits & Shamir (1977).

The Two-Loop WDN consists of one reservoir, six demand nodes, and eight pipes. Figure 3 shows the schematic of the network. The reservoir in the network has a constant head of 210 m and all the pipes have a constant length of 1,000 m. The Hazen–William coefficient is adopted as 130. The minimum pressure requirement is 30 m at all the demand nodes. Table 1 shows the nodal elevation and nodal demand data for the Two-Loop Network. Table 2 shows the available set of diameters and its corresponding unit cost.

In the paper by Alperovits & Shamir (1977), costs are given in arbitrary units. When we apply to a specific case study, specific monetary units may be given depending on the country. To generalize the study, for both benchmark problems adopted in this study costs are given in arbitrary units (Table 2).

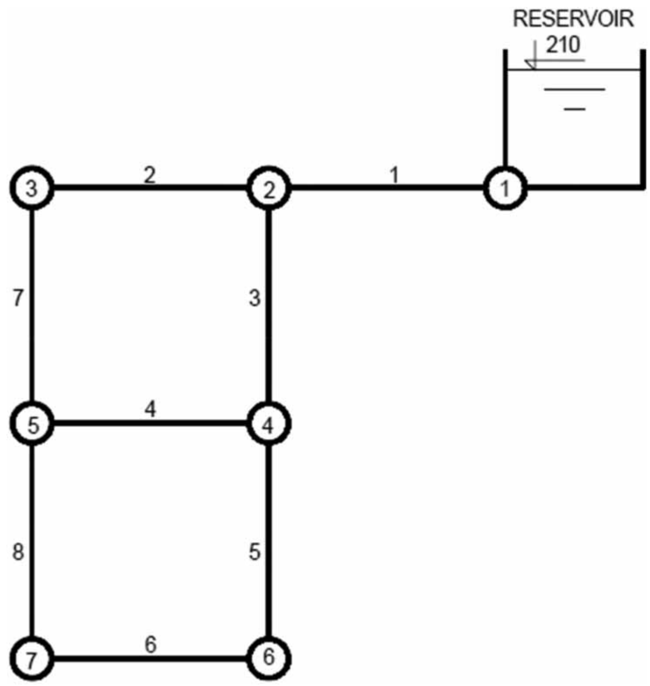



**Figure 3** | Schematic of a Two-Loop network (*Source:* Savic & Walters 1997).

**Table 1** | Nodal elevation and demand for the Two-Loop WDN

| Node | Elevation in m | Demand in m$^3$/h |
|---|---|---|
| 1 | 210 | −1,120 |
| 2 | 150 | 100 |
| 3 | 160 | 100 |
| 4 | 155 | 120 |
| 5 | 150 | 270 |
| 6 | 165 | 330 |
| 7 | 160 | 200 |

The network is solved using the linked simulation–optimization approach. For RCGA, tournament selection, blend crossover, and random mutation operators are used. For this study, sensitivity analysis is carried out for population size, crossover, and mutation and is shown in Tables 3–5, respectively. Sensitivity analysis is shown in Figures 4–6 as a graph between cost and iterations of different population sizes, crossover fractions, and mutation fractions.

After doing the sensitivity analysis the final input parameters of RCGA are: population size = 60; number of generations = 100; crossover probability = 0.7; mutation probability = 0.01.

With this optimum parameter of RCGA, the results obtained from the present study (RCGA) and the results reported in the past are shown in Table 6. Eight pipes are in the network and hence 14 possible pipe diameters, the size of decision space is $14^8$. From Table 6 it is clear that the number of function evaluations is less and thereby computational time is less in the present study compared to the past results. This necessitates the need for sensitivity analysis and

**Table 2** | Available set of diameters with unit cost for the Two-Loop WDN

| Diameter (inches) | Cost (unit/m) |
|---|---|
| 1 | 2 |
| 2 | 5 |
| 3 | 8 |
| 4 | 11 |
| 6 | 16 |
| 8 | 23 |
| 10 | 32 |
| 12 | 50 |
| 14 | 60 |
| 16 | 90 |
| 18 | 130 |
| 20 | 170 |
| 22 | 300 |

1 inch = 2.54 cm.

**Table 3** | Sensitivity analysis for the population size

| Population size | Number of generations | Total cost (unit) | Optimal cost at *i*th iteration |
|---|---|---|---|
| 20 | 100 | 572,000 | 17 |
| 30 | 100 | 475,000 | 14 |
| 40 | 100 | 443,000 | 19 |
| 60 | 100 | 419,000 | 23 |

**Table 4** | Sensitivity analysis for crossover

| Crossover (pc) | Total cost (unit) | Optimal cost at *i*th iteration |
|---|---|---|
| 0.6 | 419,000 | 25 |
| 0.7 | 419,000 | 23 |
| 0.8 | 428,000 | 19 |
| 0.9 | 446,000 | 28 |

**Table 5** | Sensitivity analysis for mutation

| Mutation (pm) | Total cost (unit) | Optimal cost at *i*th iteration |
|---|---|---|
| 0.01 | 419,000 | 23 |
| 0.02 | 424,000 | 13 |
| 0.03 | 428,000 | 19 |
| 0.04 | 450,000 | 34 |

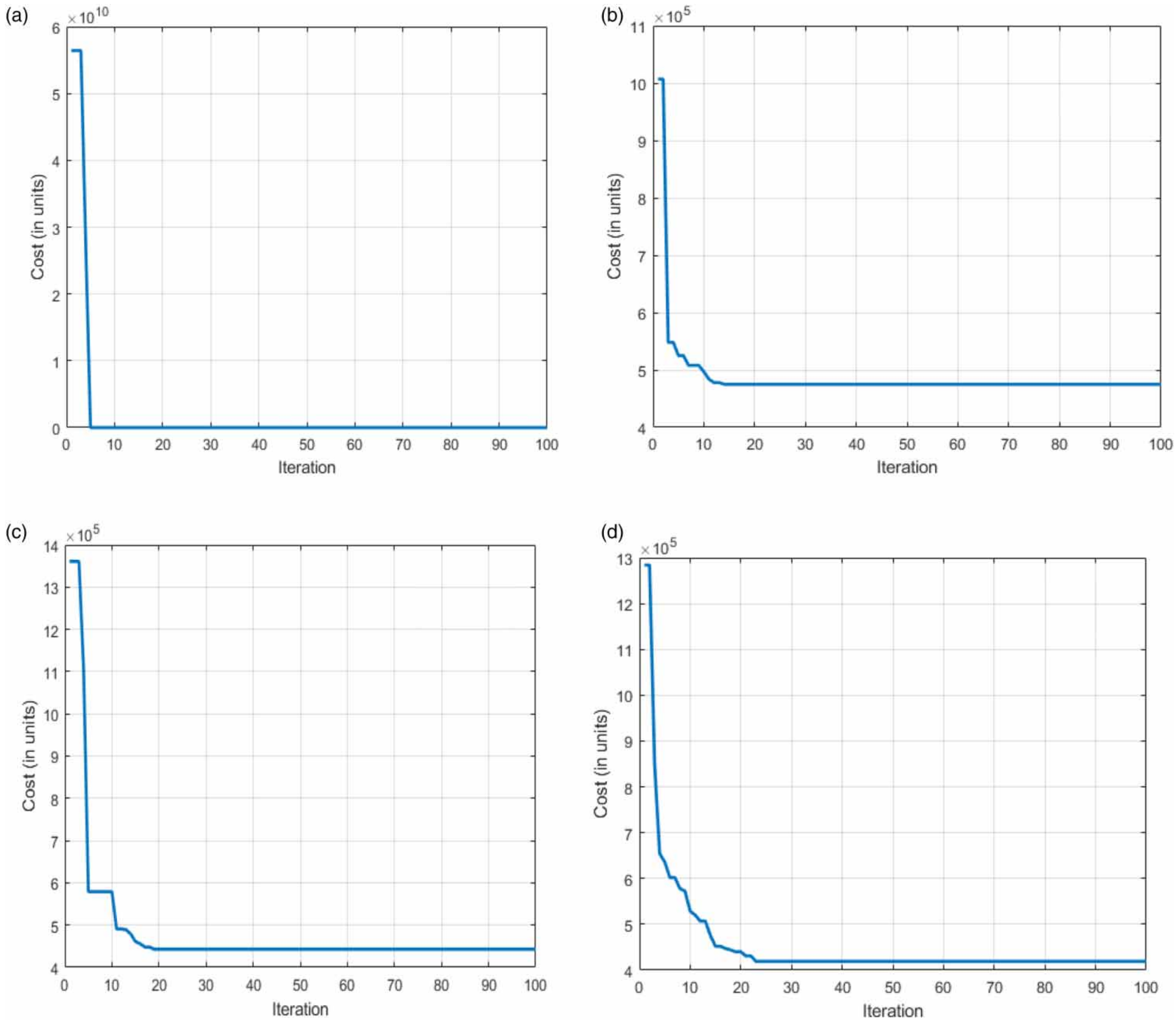



**Figure 4** | Cost and iterations for various population sizes: (a) population size = 20; (b) population size = 30; (c) population size = 40; and (d) population size = 60.

optimizing the parameters of the optimization module in a simulation–optimization scheme. Figure 7 shows the convergence of the fitness function of RCGA versus iterations over a single run. The optimal cost of 419,000 units is reached at 23$^{th}$ iteration. Savic & Walters (1997) used GA for the least-cost design of the same WDN, and the total number of

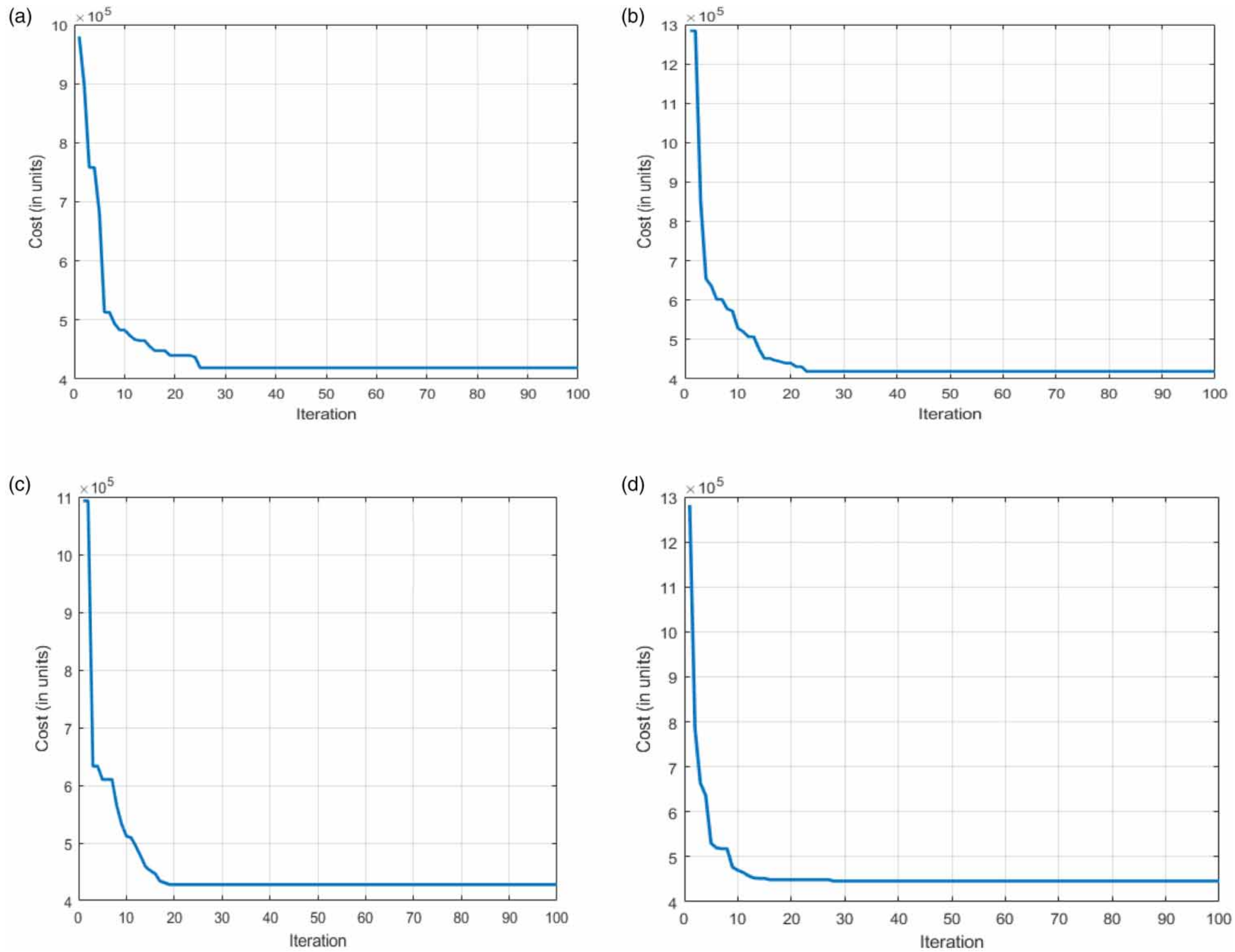



**Figure 5** | Cost and iterations for various crossover probability: (a) pc = 0.6; (b) pc = 0.7; (c) pc = 0.8; (d) pc = 0.9.

function evaluations to get the optimal solution was reported to be approximately 6,750. Cunha & Sousa (1999) used simulated annealing and Suribabu & Neelakantan (2006) used PSO coupled with EPANET for the design of WDN and the number of function evaluations reported was 5,138. The study reported by Rao *et al.* (2017) used the FEM-PSO simulation–optimization technique and the number of function evaluations was 7,400. RCGA methodology used in this study found that the optimal cost obtained was exactly matching with the results reported in the past. RCGA-based methodology used in the present study required only 1,380 function evaluations to obtain the optimal solution. Thus, the RCGA-based methodology is performing well. Table 7 shows the Two-Loop Network Node results such as pressure heads for optimal diameters in the present study.

### 3.2. Benchmark problem 2 – GoYang WDN

The GoYang network in South Korea was first studied by Kim *et al.* (1994). The GoYang WDN includes 22 demand nodes, thirty pipes, and one constant pump of 4.52 kW linking to one reservoir. The reservoir has a constant head of 71 m. The Hazen–Williams head-loss equation is adopted with the roughness coefficient value for each pipe as 100. The minimum pressure head above the ground elevation of each node is maintained at 15 m. The schematic of the network is shown in Figure 8. The nodal elevation and nodal demand data for the GoYang network are given in Table 8. The data of the commercially available set of diameters and its corresponding unit cost are given in Table 9.

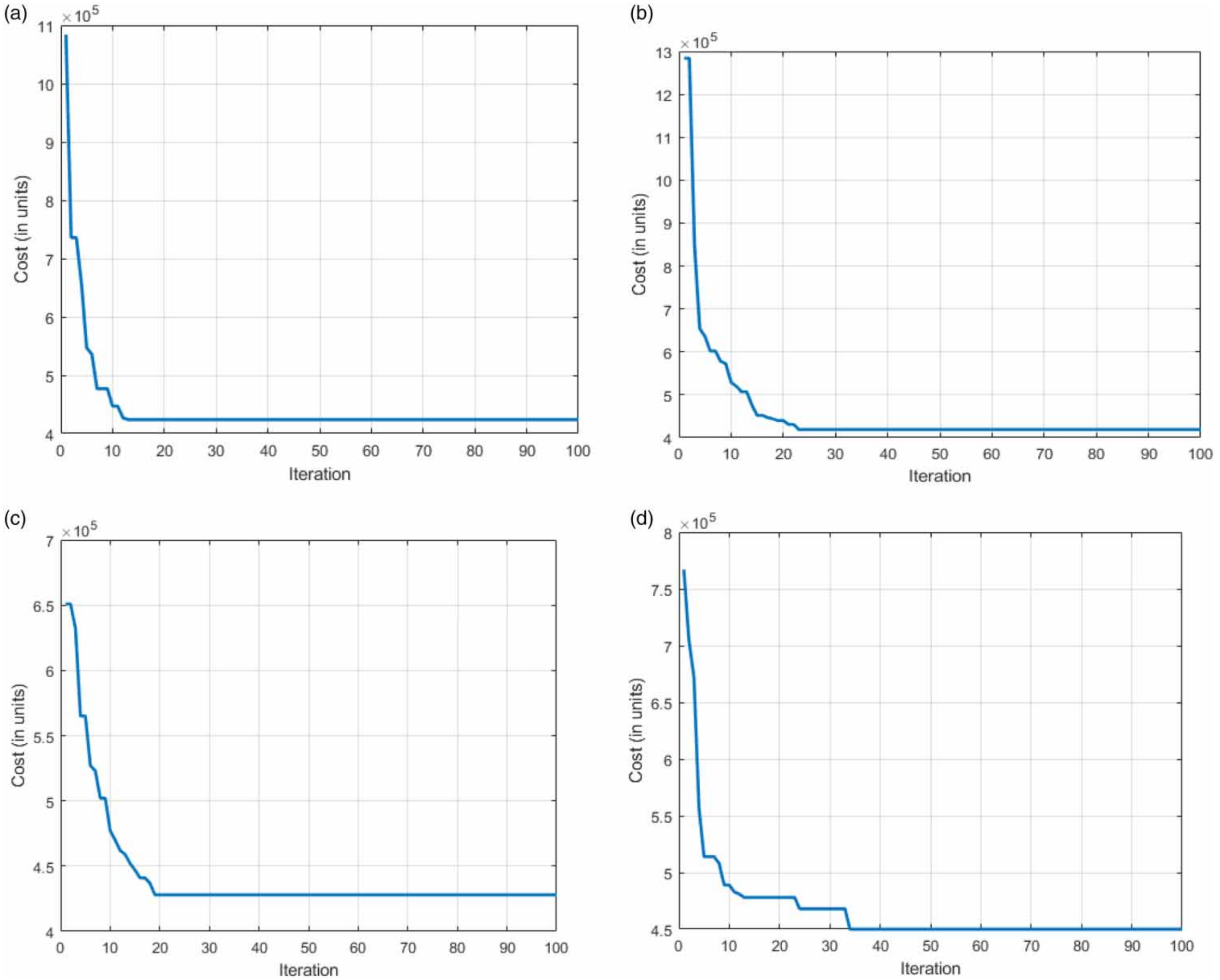



**Figure 6** | Cost and iterations for various mutation probabilities: (a) pm = 0.01; (b) pm = 0.02; (c) pm = 0.03; (d) pm = 0.04.

**Table 6** | Results of the Two-Loop WDN

| Pipe no. | Savic & Walters (1997) Diameter (inches) | Cunha & Sousa (1999) Diameter (inches) | Suribabu & Neelakantan (2006) Diameter (inches) | Rao *et al.* (2017) Diameter (inches) | RCGA present study Diameter (inches) |
|---|---|---|---|---|---|
| 1 | 18 | 18 | 18 | 18 | 18 |
| 2 | 10 | 10 | 10 | 10 | 10 |
| 3 | 16 | 16 | 16 | 16 | 16 |
| 4 | 4 | 4 | 4 | 4 | 4 |
| 5 | 16 | 16 | 16 | 16 | 16 |
| 6 | 10 | 10 | 10 | 10 | 10 |
| 7 | 10 | 10 | 10 | 10 | 10 |
| 8 | 1 | 1 | 1 | 1 | 1 |
| Optimal cost (unit) | 419,000 | 419,000 | 419,000 | 419,000 | 419,000 |
| Number of function evaluation | 6,750 | – | 5,138 | 7,400 | 1,380 |

1 inch = 2.54 cm

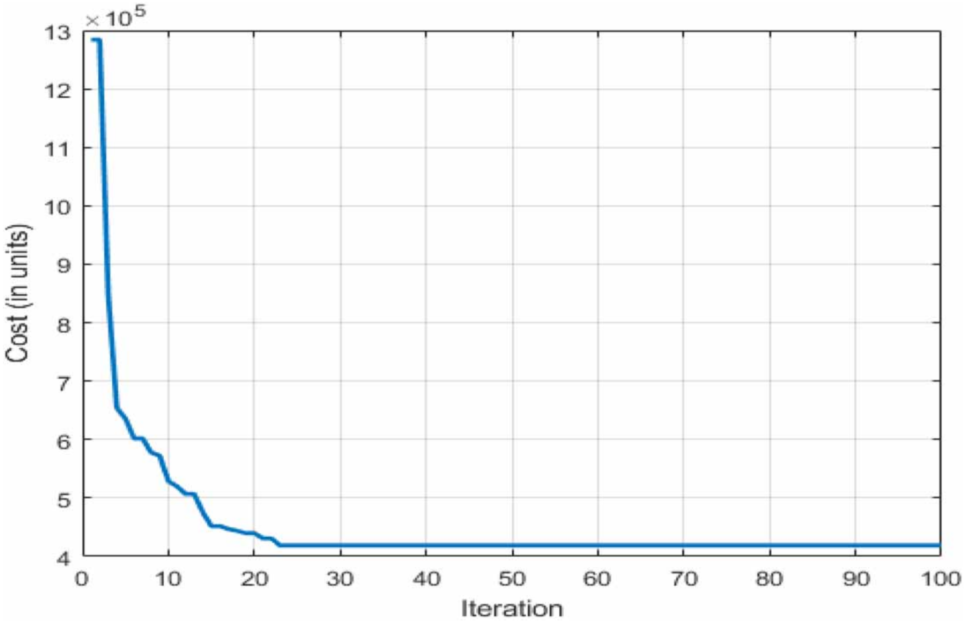



**Figure 7** | Convergence of RCGA for Two-Loop Network showing reduction cost (in units) over the iterations.

**Table 7** | Two-Loop network node results for optimal diameters for RCGA approach

| Node ID | Head (m) | Pressure (m) |
|---|---|---|
| Junction 2 | 203.24 | 53.24 |
| Junction 3 | 190.61 | 30.61 |
| Junction 4 | 200.52 | 45.52 |
| Junction 5 | 184.07 | 34.07 |
| Junction 6 | 197.52 | 32.52 |
| Junction 7 | 192.62 | 32.62 |
| Reservoir 1 | 210 | 0.00 |

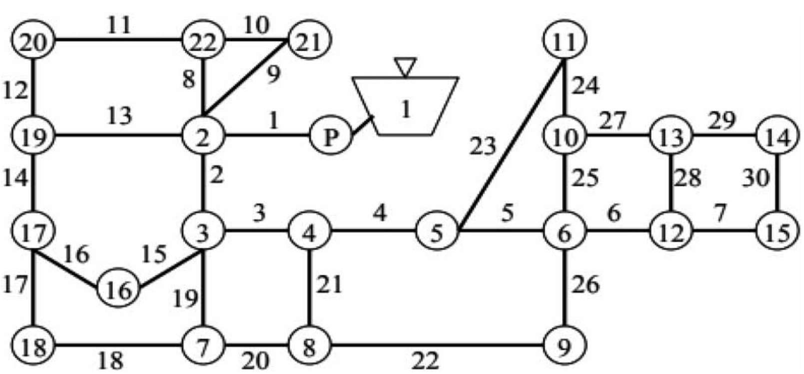


**Figure 8** | Schematic of GoYang WDN (*Source:* Geem 2006).

**Table 8** | Nodal elevation and demand for the GoYang WDN

| Node | Elevation in m | Demand in $m^3$/day | Node | Elevation in m | Demand in $m^3$/day |
|---|---|---|---|---|---|
| 1 | 71 | −2,550 | 12 | 58.6 | 37.5 |
| 2 | 56.4 | 15 | 13 | 59.3 | 37.5 |
| 3 | 53.8 | 70.5 | 14 | 59.8 | 63 |
| 4 | 54.9 | 58.5 | 15 | 59.2 | 445.5 |
| 5 | 56 | 75 | 16 | 53.6 | 108 |
| 6 | 57 | 67.5 | 17 | 54.8 | 79.5 |
| 7 | 53.9 | 63 | 18 | 55.1 | 55.5 |
| 8 | 54.5 | 48 | 19 | 54.2 | 118.5 |
| 9 | 57.9 | 42 | 20 | 54.5 | 124.5 |
| 10 | 62.1 | 30 | 21 | 62.9 | 31.5 |
| 11 | 62.8 | 42 | 22 | 61.8 | 799.5 |

**Table 9** | Available set of diameters with cost for the GoYang WDN

| Sr.No | Diameter (mm) | Cost (unit/m) |
|---|---|---|
| 1 | 80 | 37,890 |
| 2 | 100 | 38,933 |
| 3 | 125 | 40,563 |
| 4 | 150 | 42,554 |
| 5 | 200 | 47,624 |
| 6 | 250 | 54,125 |
| 7 | 300 | 62,109 |
| 8 | 350 | 71,524 |

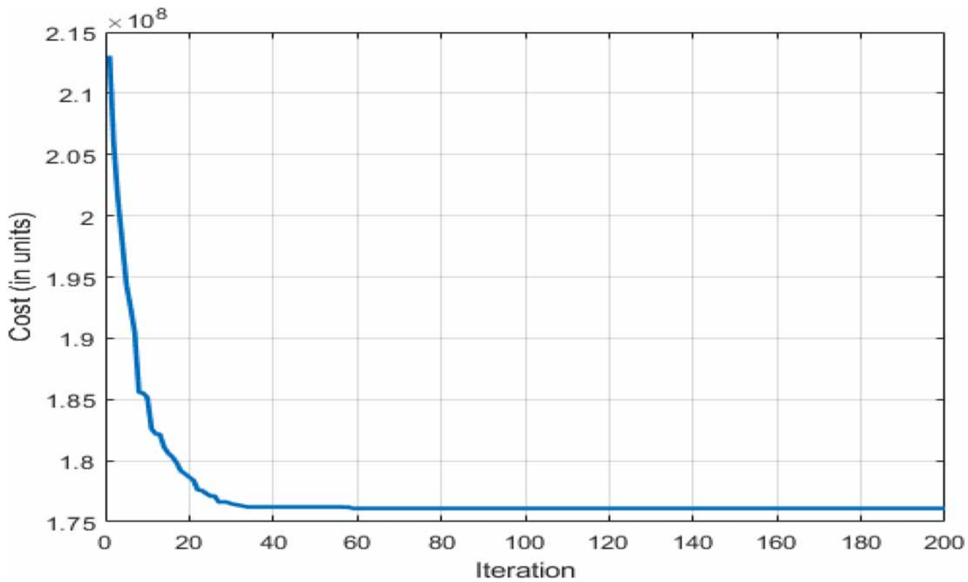



**Figure 9** | Convergence of RCGA for the GoYang network showing reduction in cost (in units) over the iterations.

**Table 10** | Results for the GoYang network

| Pipe no. | Pipe length (m) | Original diameter (mm) | Kim *et al.* (1994) diameter (mm) | Geem (2006) diameter (mm) | Present study (RCGA) diameter (mm) |
|---|---|---|---|---|---|
| 1 | 165 | 200 | 200 | 150 | 80 |
| 2 | 124 | 200 | 200 | 150 | 125 |
| 3 | 118 | 150 | 125 | 125 | 125 |
| 4 | 81 | 150 | 125 | 150 | 125 |
| 5 | 134 | 150 | 125 | 100 | 80 |
| 6 | 135 | 100 | 100 | 100 | 100 |
| 7 | 202 | 80 | 80 | 80 | 80 |
| 8 | 135 | 100 | 80 | 100 | 80 |
| 9 | 170 | 80 | 80 | 80 | 80 |
| 10 | 113 | 80 | 80 | 80 | 80 |
| 11 | 335 | 80 | 80 | 80 | 80 |
| 12 | 115 | 80 | 80 | 80 | 80 |
| 13 | 345 | 80 | 80 | 80 | 80 |
| 14 | 114 | 80 | 80 | 80 | 80 |
| 15 | 103 | 100 | 80 | 80 | 80 |
| 16 | 261 | 80 | 80 | 80 | 80 |
| 17 | 72 | 80 | 80 | 80 | 80 |
| 18 | 373 | 80 | 100 | 80 | 80 |
| 19 | 98 | 80 | 125 | 80 | 80 |
| 20 | 110 | 80 | 80 | 80 | 80 |
| 21 | 98 | 80 | 80 | 80 | 80 |
| 22 | 246 | 80 | 80 | 80 | 80 |
| 23 | 174 | 80 | 80 | 80 | 100 |
| 24 | 102 | 80 | 80 | 80 | 80 |
| 25 | 92 | 80 | 80 | 80 | 80 |
| 26 | 100 | 80 | 80 | 80 | 100 |
| 27 | 130 | 80 | 80 | 80 | 100 |
| 28 | 90 | 80 | 80 | 80 | 80 |
| 29 | 185 | 80 | 100 | 80 | 80 |
| 30 | 90 | 80 | 80 | 80 | 80 |
| Total cost (unit) | – | 179,428,600 | 179,142,700 | 177,135,800 | 176,098,456 |
| Number of function evaluation | – | – | – | 10,000 | 8,850 |

Similar to the Two-Loop network, sensitivity analysis was carried out for the GoYang WDN and the input parameters chosen are: population size = 150; number of generations = 200; crossover probability = 0.8; mutation probability = 0.01. tournament selection, blend crossover and random mutation operators are used in this study.

The size of the decision space is $8^{30}$ (8 being the number of available pipe diameters and 30 being the number of pipes in the network). Figure 9 shows the convergence of the fitness function of RCGA versus iterations over a single run. The optimal cost is reached at 59th iteration. The results obtained from the present study and results reported in past are shown in Table 10. The number of function evaluations required to obtain the optimal solution is 8,850. From the literature it is observed that the original cost of the network is 179,428,600 units. Kim *et al.* (1994) used nonlinear programming and obtained an optimum cost of 179,142,700 units, Geem (2006) used a harmony search algorithm and obtained an optimal

**Table 11** | Node (pressure) results for optimal diameters for the GoYang network

| Node | Present study (RCGA) pressure (m) | Node | Present study (RCGA) pressure (m) |
|---|---|---|---|
| 1 | 26.62 | 12 | 17.38 |
| 2 | 26.33 | 13 | 1,522 |
| 3 | 24.32 | 14 | 15.35 |
| 4 | 23.17 | 15 | 26.07 |
| 5 | 20.68 | 16 | 24.69 |
| 6 | 26.04 | 17 | 24.4 |
| 7 | 24.72 | 18 | 25.28 |
| 8 | 19.9 | 19 | 24.54 |
| 9 | 15.34 | 20 | 17.52 |
| 10 | 15.62 | 21 | 17.18 |
| 11 | 18.1 | 22 | 0 |

cost of 177,135,800 units, whereas the present study using RCGA optimal cost is obtained as 176,098,456 unit. Geem (2006) used harmony search to obtain the optimum network and 10,000 function evaluations were required; whereas in the present study using RCGA, only 8,850 function evaluations were required to obtain the optimal solution. In the present study, the optimal cost and the number of function evaluation is less compared to other methods. Table 11 shows the node pressure for optimal diameters for the GoYang network for the present study.

## 4. CONCLUSIONS

Research related to the least-cost design of WDNs is presented in this study. RCGA and EPANET were considered as the optimization module and simulation module, respectively. The developed model is applied to two benchmark WDN problems, i.e Two-Loop and GoYang networks. It was found that the RCGA approach is a good tool after parameter optimization for the least-cost design of WDN as the results obtained from the application of the RCGA methodology for the two benchmark networks proved that RCGA can give optimal solutions with less function evaluation. The number of function evaluations will increase with increasing complexity of the system. For very complex systems with large numbers of pipes, it is suggested to use RCGA as the optimization module. RCGA are useful when the search space is very large and there are a large number of parameters involved. In reallife, WDNs are large and the search space of decision parameters (pipe diameter) is therefore also large. The advantage of RCGA is that uncertainty in demand and optimal positioning of the tank/reservoir can be easily incorporated into the model. For future studies, a real case study can be used to check the computational efficiency and also to include multiple objectives. Also, the metaheuristic algorithms Grass Hopper Optimization Algorithm, Sparrow Search Algorithm, and Artificial Bee Colony Algorithm can be applied to the benchmark problems and their computational efficiency checked in the simulation–optimization framework.

## AUTHOR CONTRIBUTIONS

V.H.S.K. did formal assessment and was involved in conceptualization, data collection, framework of methodology, model development, and software analysis. S.K.P. did formal assessment, conceptualized, performed methodology, collected resources, and was involved in supervision, initial draft writing, review, and editing.

## DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

## CONFLICT OF INTEREST

The authors declare there is no conflict.

## REFERENCES


Alperovits, E. A. & Shamir, U. 1977 Design of optimal water distribution systems. *Water Resources Research* **13** (6), 885–900.

Batista do Egito, T., de Azevedo, J. R. G. & Marques Bezerra, S. D. T. 2023 Optimization of the operation of water distribution systems with emphasis on the joint optimization of pumps and reservoirs. *Water Supply* **23** (3), 1094–1105. https://doi.org/10.2166/ws.2023.065.

Bhave, P. 1988 Calibrating water distribution network models. *Journal of Environmental Engineering* **114** (1), 120–136.

Broad, D. R., Dandy, G. C. & Maier, H. R. 2005 Water distribution system optimization using metamodels. *Journal of Water Resources Planning and Management, ASCE* **131** (3), 172–180.

Broad, D. R., Maier, H. R. & Dandy, G. C. 2010 Optimal operation of complex water distribution systems using metamodels. *Journal of Water Resources Planning and Management, ASCE* **136** (4), 433–443.

Cesario, L. 1995 *Modeling, Analysis, and Design of Water Distribution Systems*. American Water Works Association, Denver, CO.

Chiplunkar, A. V., Mehndiratta, S. L. & Khanna, P. 1986 Looped water distribution system optimization for single loading. *Journal of Environmental Engineering* **112** (2), 265–279.

Chen, L., Wu, T., Wang, Z., Lin, X. & Cai, Y. 2023 A novel hybrid BPNN model based on adaptive evolutionary Arti ficial Bee Colony algorithm for water quality index prediction. *Ecological Indicators* **146**, article 109882, 1–15.

Cunha, M. C. & Sousa, J. 1999 Water distribution network design optimization: Simulated annealing approach. *Journal of Water Resources Planning and Management* **125** (4), 215–221.

Dandy, G. C., Simpson, A. R. & Murphy, L. J. 1996 An improved genetic algorithm for pipe network optimization. *Water Resources Research* **32** (2), 449–458.

Eiger, G., Shamir, U. & Ben-Tal, A. 1994 Optimal design of water distribution networks. *Water Resources Research* **30** (9), 2637–2646.

Geem, Z. W. 2006 Optimal cost design of water distribution networks using harmony search. *Engineering Optimization* **38** (3), 259–280.

Goldberg, D. 1989 *Genetic Algorithms for Search, Optimization and Machine Leaning*. Addison-Wesley Publishing Co., Massachusetts.

Goldberg, D., Sastry, K. & Kendall, G. 2005 Chapter 4. Genetic Algorithms. In: *Search Methodologies. Introductory Tutorials in Optimization and Decision Support Techniques* (Burke, E. K. & Kendall, G. (eds.)). Springer, New York, NY, pp. 97–125.

Gupta, I., Gupta, A. & Khanna, P. 1999 Genetic algorithm for optimization of water distribution systems. *Environmental Modelling & Software* **4**, 437–446.

Kanakoudis, V. 2004 A troubleshooting manual for handling operational problems in water pipe networks. *Water Supply: Research & Technology-AQUA* **53** (2), 109–124.

Kessler, A. & Shamir, U. 1989 Analysis of the linear programming gradient method for optimal design of water supply networks. *Water Resources Research* **25** (7), 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** (4), 59–67.

Lansey, K. E. & Mays, L. M. 1989 Optimal design of water distribution system. *Journal of Hydraulic Engineering* **115** (10), 1401–1418.

Mala-Jetmarova, H., Sultanova, N. & Savic, D. 2017 Lost in optimization of water distribution systems? A literature review of system operation. *Environmental Modelling and Software* **93**, 209–254.

Mohan, S., Sreejith, P. K. & Pramada, S. K. 2007 Optimization of open-pit mine depressurization system using simulated annealing technique. *Journal of Hydraulic Engineering* **133**, 825–830. https://doi.org/10.1061/(ASCE)0733-9429(2007)133:7(825).

Pramada, S. K., Minnu, K. P. & Roshni, T. 2018a Insight into seawater intrusion due to pumping: A case study of Ernakulam coast, India. *ISH Journal of Hydraulic Engineering* **27** (4), 2164–2304.

Pramada, S. K., Mohan, S. & Sreejith, P. K. 2018b Application of genetic algorithm for the groundwater management of a coastal aquifer. *ISH Journal of Hydraulic Engineering* **24** (2), 124–130.

Rao, C. J., Jothiprakash, V. & Eldho T, I. 2017 Design of a pipe network using the finite element method coupled with particle-swarm optimization. *Journal of Pipeline Systems Engineering and Practice* **8** (4), 1–10.

Rossman, L. 1993 *EPANET, Users Manual*. Risk Reduction Engineering Laboratory. U.S. Environmental Protection Agency, Cincinnati, OH.

Sangroula, U., Han, K.-H., Koo, K.-M., Gnawali, K. & Yum, K.-T. 2022 Optimization of water distribution networks using genetic algorithm based SOP–WDN program. *Water* **14**, 851.

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** (2), 67–77.

Simpson, A., 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** (4), 423–443.

Suribabu, C. R. & Neelakantan, T. R. 2006 Design of water distribution networks using particle swarm optimization. *Urban Water Journal* **3** (2), 111–120. doi:10.1080/15730620600855928.

Surono, S., Goh, K. W., Onn, C., Nurraihan, A., Siregar, N., Borumand Saeid, A. & Wijaya, T. 2022 Optimization of Markov weighted fuzzy time series forecasting using genetic algorithm (GA) and particle swarm optimization (PSO). *Emerging Science Journal* **6**, 1375–1393. doi:10.28991/ESJ-2022-06-06-010.

Vairavamoorthy, K. & Ali, M. 2000 *Optimal Design of Water Distribution Systems Using Genetic Algorithms*. *Journal of Computer-Aided Civil and Infrastructure Engineering* **15**, 374–382.

Wang, Z., Wang, Q. & Wu, T. 2023 A novel hybrid model for water quality prediction based on VMD and IGOA optimized for LSTM. *Frontiers of Environmental Science & Engineering* **17**, 88. https://doi.org/10.1007/s11783-023-1688-y.

Wright, A., 1991 Genetic algorithms for real parameter optimization. In: *Foundations of Genetic Algorithms* (Rawlins, G. J. E., ed.). Morgan Kaufmann, San Mateo, CA, pp. 205–221.

Wu, Z. Y. & Simpson, A. R. 2001 Competent genetic-evolutionary optimization of water distribution systems. *Journal of Computing in Civil Engineering* **15** (2), 89–101.

Wu, Z. Y. & Simpson, A. R. 2002 A self-adaptive boundary search genetic algorithm and its application to water distribution systems. *Journal of Hydraulic Research* **40** (2), 191–203.

Yao, Z., Wang, Z., Cui, X. & Zhao, H. 2023 Research on multi-objective optimal allocation of regional water resources based on improved sparrow search algorithm. *Journal of Hydroinformatics* **25** (4), 1413–1437. https://doi.org/10.2166/hydro.2023.037.

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