Ain Shams Engineering Journal 12 (2021) 223–239

Contents lists available at ScienceDirect

Ain Shams Engineering Journal

journal homepage: www.sciencedirect.com

Civil Engineering

Global performance of metaheuristic optimization tools for water distribution networks

Berge Djebedjian [a,*], Hossam A.A. Abdel-Gawad [b], Riham M. Ezzeldin [b]

[a] Mechanical Power Engineering Department, Faculty of Engineering, Mansoura University, El-Mansoura, Egypt
[b] Irrigation and Hydraulics Engineering Department, Faculty of Engineering, Mansoura University, El-Mansoura, Egypt

ARTICLE INFO

Article history:
Received 6 May 2020
Revised 25 June 2020
Accepted 3 July 2020
Available online 6 September 2020

Keywords:
Optimization
Algorithm performance
Water distribution networks
Metaheuristic optimization algorithms
Performance metrics

ABSTRACT

Numerous metaheuristic optimization algorithms are used for optimal design of water distribution networks. Each algorithm shows dissimilar characteristics depending on the network properties and the sensitivity analysis of the algorithm control variables. New performance metrics of metaheuristic optimization methods are proposed using simple but robust refined metrics and were applied to the available literature data for different algorithms which have previously been used for three popular benchmark water distribution networks. In general, recent performance metrics are devoted to measure effectiveness, efficiency, and reliability in a separate manner, which made some confusion, which is the best?. In the present work, the proposed metrics are used to calculate both of best global and average global performance of different optimization algorithms. The results show that the present metrics have a good distinctive performance between different algorithms. The Fittest individual referenced Differential Evolution is found to be the best algorithm.

1. Introduction

Performance evaluation of water distribution systems includes either analysis of the results of optimization tools used for the optimal design which is the subject of the present study or evaluation of water quality and quantity in the network (Shahzad et al. [1]; Zhang [2]) or water shortage and lack of pressure (Basmenji et al. [3]).

The evolutionary algorithms (EAs) have many advantages (e.g., finding a global solution, easy link with simulation models, and straightforward for solving discrete decision variables problems) and potential challenges with both computational efficiency and adjustment of searching behavior (Maier et al. [4]).

The performance evaluation of different metaheuristic optimization algorithms for water distribution networks (WDNs) has been reported in many researches. General recent reviews on the subject of water distribution network optimization can be found in Ruiz-Vanoye et al. [5], Mala-Jetmarova et al. [6], and Savić et al. [7]. The comparison of evolutionary multiobjective optimization algorithms in optimum design of WDNs (e.g., Monsef et al. [8]) and the comparison of water distribution system design reliability (i.e., mechanical and hydraulic) using multiobjective optimization (e.g., Atkinson et al. [9]) are beyond the present study.

The evaluation of EAs is usually measured by two important metrics: the efficiency and effectiveness. Many efficiency metrics exist in EA, such as population size, number of termination generation, space complexity, and time complexity. Hao et al. [10] stated that evaluating or comparing EAs with one of these metrics or using them separately is unfair. They studied the relationship of efficiency metrics and gave proper metrics combination. In addition, they studied the relationship between efficiency and effectiveness. They concluded that not only EAs can be compared, but also problems hardness can be measured which is concerned only with the minimum design cost.

Gomes et al. [11] proposed a methodology for the comparison of metaheuristic optimization algorithms by using a single probabilistic metric (P_{better}). In a single run, P_{better} gives the probability that a proposed algorithm produces a smaller (global?) minimum than an existing algorithm. P_{better} is based on averages, standard

* Corresponding author.
E-mail addresses: bergedje@mans.edu.eg (B. Djebedjian), hossamaaa@mans.edu.eg (H.A.A. Abdel-Gawad), eng_ezzeldin@mans.edu.eg (R.M. Ezzeldin).

Peer review under responsibility of Ain Shams University.

Production and hosting by Elsevier

https://doi.org/10.1016/j.asej.2020.07.012
2090-4479/

Nomenclature

$C_{avg\text{-}min}$	average minimum cost
C_i	Hazen-Williams coefficient for pipe i
C_{max}	maximum cost of the network using the maximum diameter for all pipes
C_{min}	minimum cost
C_{opt}	optimal cost
C_{worst}	worst solution cost
D_i	diameter of pipe i
L_i	length of pipe i
$N_{avg\text{-}eval}$	average minimum function evaluations to find the best solutions
$N_{com\text{-}pipes}$	number of available commercial pipe sizes
N_{gen}	total number of evaluations (generations)
N_{iter}	iteration number
$N_{max.iter}$	number of maximum iterations
$N_{obj\text{-}eval}$	minimum number of objective function evaluations
N_p	number of pipes of the network
N_{search}	number of searches (population size)
N_{sim}	total number of simulations
N_{space}	total solution space (search space size)
$N_{success}$	number of achievements of optimal cost
q_i	flow in pipe i
α, β	exponents in the Hazen-Williams formula
$\eta_{algorithm}$	global algorithm efficiency
$\eta_{avg\text{-}algorithm}$	average global algorithm efficiency
$\eta_{avg\text{-}cost}$	average effectiveness
$\eta_{avg\text{-}eval}$	average evaluation efficiency
η_{cost}	cost efficiency
η_{eval}	evaluation efficiency
η_{gen}	generation efficiency
$\eta_{gen\text{-}success}$	generation-success efficiency
η_{iter}	iteration efficiency
$\eta_{success}$	success efficiency
ω	conversion factor in the Hazen-Williams formula

deviations, best/worst results, and minimum objective function values obtained during the algorithms runs. Therefore, a global comparison between algorithms is achieved by computing P_{better} for different numbers of objective function evaluations and runs.

Zecchin et al. [12] tested the performance of five different ant colony optimization (ACO) algorithms on some standard water distribution systems (WDS) case studies. They reported that the Max-Min Ant System (MMAS) and elitist-rank ant system algorithms outperform all other algorithms applied to their case studies in the literature.

Dandy et al. [13] introduced a methodology for the accurate comparison of different algorithms for the optimum design of WDNs. The different algorithms were compared in terms of (a) the "optimum solution" obtained; (b) the convergence speed; and (c) the spread and consistency of the solutions obtained over a large number of random starting seeds and numbers of evaluations. The genetic algorithms (GA), particle swarm optimization (PSO) and differential evolution (DE) were applied to two water distribution networks (the New York tunnels and Hanoi network). The obtained results indicated that GA gives the best performance in terms of the mean objective function, but that DE offers considerable potential for achieving highly reliable solutions. PSO tends to converge rapidly to solutions that are not as good as those obtained by the other techniques.

Zheng et al. [14] presented a systematic performance comparison between the DE algorithm and the genetic algorithms (GAs). Two DE variants (traditional DE, and dither DE) and two GA variants (traditional GA and creeping mutation GA) were compared in terms of optimizing the design of two WDNs (New York tunnels and Hanoi network). Their results showed that the DE variants significantly outperform the GA variants in terms of both the solution quality and efficiency.

Mora-Melià et al. [15–18] studied the performance of four EAs: (1) PseudoGenetic Algorithm (PGA); (2) PSO; (3) harmony search (HS); and (4) Shuffled Frog Leap Algorithm (SFLA), on four medium benchmarks WDNs (GoYang, Hanoi, R-9 Joao Pessoa, and New York Tunnels). Control and tuning parameters of these algorithms were studied in detail with more than 25,000 runs for every combination of any algorithm (with various ranges of parameters) and WDN. They found that calibration of different parameters of each EA is an essential step to get its optimal efficiency; i.e. improves the algorithm performance till 250% with respect to using uncalibrated parameters. Both of PGA and SELA performed better than the remaining two EAs for the four WDNs.

El-Ghandour and Elbeltagi [19] performed a comparison for the performance of five EAs (GA, PSO, ACO, Memetic Algorithm (MA), and SFLA) for the design optimization of the two-loop network and rehabilitation of the New York tunnels network. Contrary to Mora-Melia et al. [15–18] and Dandy et al. [13], their results clarified that the PSO performance is the best in comparison with the other four EAs with regard to the best results, number of objective function evaluations, convergence speed, and efficiency rate. They repeated every combination of EA and WDN fifty times with different initial random seeds, but with constant values of control and tuning parameters that were borrowed from the literature. That contradiction led to conclude that overall considerations of all parameters and different formulations/forms of any EA is an inevitable process to compare between different EAs. Unfortunately, this requires nearly unlimited computational cost.

Moosavian and Lence [20] compared ten different techniques based on EAs for least-cost design of WDNs. The ten EAs were applied to the design of three networks under different stopping criteria of algorithms. For the two-loop network, the results showed that the particle swarm optimization gravitational search (PSOGSA) and biology and bioinformatics global optimization (MEIGO) algorithms efficiently converged to the global optimum, but performed poorly for large networks.

The present paper introduces two practical innovative global performance metrics of metaheuristic optimization methods applied to WDNs, which enable of selecting the best performed algorithm for a specified WDN. Depending on the available literature data these metrics can be used as: (1) global performance metric, if only the optimal run is considered; and (2) average global performance metric, if several runs are considered. Global performance merges four categories of performance (i.e., effectiveness, efficiency, evaluation efficiency, and reliability) that may have a conflict response for the same algorithm. The remaining part of the paper consists of six sections. Sections 2 and 3 are devoted to categories of different metaheuristic optimization algorithms and review of previous performance metrics used in the literature, respectively. Details and illustrative discussion of different performance metrics and the two proposed global performance ones are presented in Section 4. Three benchmark WDNs and their properties are illustrated in Section 5, and analysis of all available literature data considered these WDNs are presented in Section 6. Finally, the conclusions and recommendations of the paper are settled in Section 7.

2. Heuristic optimization algorithms

Computational intelligence optimization algorithms afford solutions when the derived mathematical model is constituted from various types of objective functions, constraint functions, and decision variables. These algorithms efficiently obtain the optimum solutions within an acceptable computational time. These algorithms are iterative methods and can be categorized to ten different inspiration fields such as biology, chemistry, mathematics, music, physics, plant, sociology, sports, swarm, and water, Alatas [21]. In addition, there are hybrid methods as combinations of these previous based methods.

The metaheuristics technique (Vasant et al. [22]) has three types: (a) *Point-based*: They focus on a single solution at the start and then moves away from it, drawing a trajectory within the search space (e.g., Simulated Annealing SA, Tabu Search TS); (b) *Population-based*: They focus on a set of solutions instead of a single solution (e.g., GA, DE, PSO); and (c) *Hybrid optimization*: They are the combination of various point-based or population-based metaheuristics. This combination can improve algorithm performance by benefiting from the advantages and strengths of each used algorithm.

Several encouraging aspects of using the stochastic heuristic methods are: (a) the simplicity to implement, although careful implementation is required in some cases to guarantee the efficient handling of equality and inequality constraints; (b) their underlying principles contain some particular operators (e.g., elitism, parallelism, selection with probability-based acceptance) which enable wider exploration of the solutions space; and (c) the capability to be hybridized to benefit from the different characteristics of two or more methods, Chicco and Mazza [23].

Numerical studies of different evolutionary optimization techniques used for the optimization of water distribution networks are very common, De Corte and Sörensen [24]. The numerous optimization techniques applied to the optimization of WDNs and enhancing the efficiency of such techniques through hybridization are shown in Table 1.

Setting the parameters of optimization algorithms is achieved by sensitivity analysis to reach their best values. Each optimization algorithm has its number of parameters (e.g., 6 for SCE, 5 for ACO and GA, 4 for CE, PSO, SA, and SFLA, 3 for HS, IMBA, SLC, and SS, and 2 for DE and GSA), Fallah et al. [41]. It must be noted that the computational cost for the sensitivity analysis of evolutionary algorithms (EAs) parameters is ignored in the present paper due to the unavailability of data in the literature.

3. Performance evaluation of optimization methods

The quantitative evaluation of single-objective optimization problems is achieved by repeating the individual runs many times, with each run using large numbers of function evaluations, N_{gen}, for each problem. The comparison of the results of different metaheuristics is difficult because the use of a fixed number of iterations as the stop criterion in the runs is not reasonable as the population-based methods (e.g., GA) would need more runtime than non-population-based ones (e.g., SA). In general, the number of evaluations, N_{gen}, is dependent on the network complexity and the algorithm, while the search space is dependent on the number of pipes, N_p, and the number of available pipe diameters, $N_{com\text{-}pipes}$. Reca et al. [75] presented the ratio between the number of evaluations in two networks with different search spaces by adopting $N_{gen} = N_p.\ln(N_{com\text{-}pipes})$.

The performance evaluation of optimization methods are achieved using many profiles and metrics such as: (a) Performance profiles present efficiency, robustness, and probability of success in a graphically compact form, Dolan and Moré [76]; (b) Accuracy profiles give a visualization of an entire optimization benchmarking test of fixed-cost data set; (c) Data profiles proposed by Moré and Wild [77] to adjust the performance profiles for derivative-free optimization algorithms; and (d) Statistical metrics (e.g., the mean, worst, and best costs obtained from the algorithm). Large number of runs are performed for excluding the biased performance of better initial solutions. The obtained solution quality is represented by the mean cost, which is the averaged cost of the obtained costs from the algorithm, due to repeated runs. Worst cost indicates the average of worst solutions. Finally, best cost is the best solution obtained from the algorithm runs. These metrics are usable only when the optimal cost is known. The three performance metrics are used to compare algorithms' performances.

Additionally, there are different numbers and ratios well-known in the optimization as: (a) Success rate, which is the ratio of the runs in which the optimal cost is found to the total runs made, and represents the reliability of algorithm performance. An algorithm with high success rate has higher possibility of finding near-optimal solution than the algorithm with low success rate; and (b) Mean number of function evaluations, which is the mean of the number of function evaluations at which the best solution is found during the total runs, and indicates the search efficiency.

4. Performance evaluation of optimization methods in WDNs

The evaluation of an optimization algorithm is vital due to the required computational efforts. The objective function evaluation is the call to the hydraulic simulation of the water distribution network.

Three types of data are borrowed from the litruture to evaluate different performance metrics studied in the present section as: (1) WDN data (total solution space, optimal cost); (2) specified parameters of the algorithm (number of population size, number of maximum iterations, total number of random seeds used in the calculations); and (3) the optimization results (minimum number of objective function evaluations to global best solution, number of achievements of optimal cost in case of considering several runs).

It is worth mentioning that the run time of computation is not included in the above-mentioned definitions as it depends on the structure of algorithm and computer facilities (number of processors, RAM, etc.). Therefore, it may be considered an insufficient measure for comparing between performances of different optimization algorithms. However, the number of objective function evaluations is the stopping criterion of the optimization algorithm, so it is considered in the optimization algorithm efficiency.

Each WDN has its maximum network optimization metrics according to the known optimal cost and other data from the literature that give the maximum performance. These metrics can be used for the comparison between different methods of optimization solving a known WDN. For new and developed optimization algorithms, their estimated network optimization metrics can be compared to the known maximum network optimization metrics to evaluate their performance.

Generally, the performance indicators fall into three categories: effectiveness, efficiency, and reliability (Solomatine [78]; Beiranvand et al. [79]).

4.1. Effectiveness

The effectiveness is a measure for the proximity of the algorithm solution to the global optimum (Solomatine [78]). There are two categories concerning the global optimal: availability of a known solution (e.g., well-known network), and no known solu-

Table 1
Metaheuristic algorithms applied to the optimization of water distribution networks.

Abbreviation	Algorithm	First Reference - Authors
Point and Population Based Algorithms		
ACO, ACOA	Ant Colony Optimization	Maier et al. [25]
B-GA	Bounded Genetic Algorithm	Reca et al. [26]
CE	Cross Entropy	Perelman and Ostfeld [27]
CFO	Central Force Optimization	Jabbary et al. [28]
CGA	Creeping mutation Genetic Algorithm	Zheng et al. [14]
cGA	convergent Genetic Algorithm	Afshar and Mariño [29]
CS	Cuckoo Search	Sheikholeslami et al. [30]
CSS	Charged System Search	Sheikholeslami et al. [31]
DE	Differential Evolution	Suribabu [32]
dDE	Dither Differential Evolution	Zheng [33]
DSO	Developed Swarm-based Optimization	Sheikholeslami and Talatahari [34]
EGA	Elitist Genetic Algorithm	Poojitha et al. [35]
FDE	Fittest individual referenced Differential Evolution	Moosavian and Lence [36]
GA	Genetic Algorithm	Simpson et al. [37]
GA_{mod}	Modified Genetic Algorithm	Neelakantan and Suribabu [38]
GENOME	Genetic Algorithm Pipe Network Optimization Model	Reca and Martínez [39]
GHEST	Genetic Heritage Evolution by Stochastic Transmission	Bolognesi et al. [40]
GSA	Gravitational Search Algorithm	Fallah et al. [41]
HBMO	Honey Bee Mating Optimization	Mohan and Babu [42]
HS	Harmony Search	Geem et al. [43]
IDPSO	Integer Discrete Particle Swarm Optimization	Ezzeldin et al. [44]
ILS	Iterated Local Search	De Corte and Sörensen [45]
IMBA	Improved Mine Blast Algorithm	Sadollah et al. [46]
MA	Memetic Algorithm	Baños et al. [47]
MBA	Mine Blast Algorithm	Sadollah et al. [46]
MdDE	Modified dither Differential Evolution	Zheng [33]
MMAS	Max-Min Ant System	Zecchin et al. [48]
PGA	Modified Pseudo-Genetic Algorithm	Mora-Melia et al. [15]
PSO	Particle Swarm Optimization	Suribabu and Neelakantan [49]
SA	Simulated Annealing	Loganathan et al. [50]
SADE	Self-Adaptive Differential Evolution	Zheng et al. [51]
SBA	Simple Benchmarking Algorithm	Shende and Chau [52]
SCE	Shuffled Complex Evolution	Liong and Atiquzzaman [53]
SDE	Standard Differential Evolution	Zheng [33]
SFLA	Shuffled Frog Leaping Algorithm	Eusuff and Lansey [54]
SGA	Standard Genetic Algorithm	Zheng et al. [14]
SLC	Soccer League Competition	Moosavian and Roodsari [55]
SS	Scatter Search	Lin et al. [56]
STA	State Transition Algorithm	Zhou et al. [57]
TS	Tabu Search	Lippai et al. [58], Fanni et al. [59]
WCA	Water Cycle Algorithm	Sadollah et al. [60]
WOA	Whale Optimization Algorithm	Moosavian and Lence [20], Ezzeldin and Djebedjian [61]
µGA	Micro-Genetic Algorithm	Djebedjian et al. [62]
Hybrid Algorithms		
AMMSFL	Adaptive Mutated Momentum Shuffled Frog Leaping	Aghdam et al. [63]
AMPSO	Accelerated Momentum Particle Swarm Optimisation	Aghdam et al. [64]
BLP-DE	Combined Binary Linear Programming and Differential Evolution	Zheng et al. [65]
CSHS	Combined Cuckoo-Harmony Search	Sheikholeslami et al. [30]
CSS-FA	Hybrid Charged System Search and Firefly Algorithm	Delir et al. [66]
FSSFL	Fractional Succedaneum Momentum Shuffled Frog Leaping	Aghdam et al. [67]
GA-ANN	Genetic Algorithm-Artificial Neural Networks	Broad et al. [68]
GA-ILP	Coupled Genetic Algorithm and Integer Linear Programming	Haghighi et al. [69]
GHEST	Genetic Heritage Evolution by Stochastic Transmission	Bolognesi et al. [40]
HD-DDS	Hybrid Discrete Dynamically Dimensioned Search	Tolson et al. [70]
ISEDPSO	Improved Sequential combination of PSO and Estimation of Distribution Algorithm (EDA)	Qi et al. [71]
NLP-DE	Combined Nonlinear Programming and Differential Evolution	Zheng et al. [72]
PEDPSO	Parallel hybridization of PSO and Estimation of Distribution Algorithm (EDA)	Qi et al. [71]
PSHS	Combined Particle-Swarm Harmony Search	Geem [73]
PSO-DE	Combined Particle Swarm Optimization and Differential Evolution	Sedki and Ouazar [74]

tions are available (e.g., real-world network) (Beiranvand et al. [79]). In the second category, the global minimum is replaced by the best-known minimum cost value for the network. The effectiveness is represented by the cost efficiency, η_{cost}, which is the ratio of the optimal cost, C_{opt}, to the minimum cost obtained from the optimization algorithm, C_{min},

$$\text{Effectiveness} = \eta_{cost} = \frac{C_{opt}}{C_{min}}, \quad \frac{C_{opt}}{C_{max}} \leqslant \eta_{cost} \leqslant 1 \tag{1}$$

where $C_{opt} \leq C_{min} \leq C_{max}$. C_{max} is the maximum cost of the network using the maximum available diameter for all the pipes of the network. When C_{min} equals C_{opt}, therefore, it is the global solution (i.e., η_{cost} = 1). A more representative expression for the effectiveness in the range of 0 and 1 is given as,

$$\text{Effectiveness} = \eta_{cost} = \frac{C_{opt}}{C_{min}} \cdot \frac{C_{max} - C_{min}}{C_{max} - C_{opt}}, \quad 0 \leqslant \eta_{cost} \leqslant 1 \tag{2}$$

On the other hand, many tested expressions have been used in the task of this research like $\eta_{cost} = (C_{max} - C_{min})/(C_{max} - C_{opt})$ with the drawback of very small difference in η_{cost} when C_{min} approaches C_{opt} (i.e., $\eta_{cost} \approx 1$); therefore, the effectiveness influence may be diminished. In addition, the expression η_{cost} = 1 –

$\log_{10}(C_{min}/C_{opt})/\log_{10}(C_{max}/C_{opt})$ decreases the evaluation of η_{cost} in comparison to the previous expression, but it is greater than the η_{cost} of Eq. (1). Consequently, Eq. (2) is used in the present study.

4.2. Efficiency

The efficiency of an optimization algorithm is the computational effort required to find a solution. In programming, there are three primary measures of efficiency: the number of fundamental evaluations, the running time, and the memory usage (Beiranvand et al. [79]). The memory usage is negligible compared with the number of function evaluations and the running time.

The computational effort (i.e., cost) is the cost of evaluating the objective function and a reasonable choice is the cost to termination (i.e., the number of objective function calls to the termination of an algorithm invocation, N_{gen}). Alternatively, there is the cost to success which is the number of objective function calls until a criterion is met which excludes the effects of termination criteria. This cost is the minimum number of objective function evaluations, $N_{obj\text{-}eval}$. The cost to success is not reflective of actual algorithm usage, (Kavetski et al. [80]), as the minimum cost of WDN must be specified to terminate the algorithm, run and in many cases, the optimum cost is not known in advance.

In metaheuristic optimization tools, namely, evolutionary and swarm-based algorithms, the running time depends on the total number of evaluations, N_{gen}, as it is the algorithm stopping condition. The latter is the multiplication of the population size, N_{search}, and the number of maximum iterations, $N_{max.iter}$, Eq. (4). The selections of N_{search} and $N_{max.iter}$ have a significant influence on the optimization algorithm performance and require tuning to obtain a better performance.

The influence of the total number of evaluations, N_{gen}, is quantified by the generation efficiency, η_{gen}. In recent optimization algorithms (e.g., the whale optimization algorithm), the total number of evaluations and especially the number of maximum iterations is important as it is used in the equations of the algorithm. In the present study, the algorithm efficiency equals the generation efficiency, η_{gen}, given as:

$$\text{Efficiency} = \eta_{gen} = 1 - \frac{\log_{10} N_{gen}}{\log_{10} N_{space}} \tag{3}$$

with

$$N_{gen} = N_{search} N_{max.iter} \tag{4}$$

$$N_{space} = N_{com\text{-}pipes}^{N_p} \tag{5}$$

$$1 \leqslant N_{gen} \leqslant N_{space} \tag{6}$$

where N_{gen} = total number of evaluations (generations), N_{search} = number of searches (population size), $N_{max.iter}$ = number of maximum iterations, N_{space} = total solution space, $N_{com\text{-}pipes}$ = number of available commercial pipe sizes, and N_p = number of pipes of the network.

The total number of generations, N_{gen}, is in the range of greater than or equal to 1 and less than or equal to the search space size, N_{space}, Eq. (6). It is worth noting that as the total solution space, N_{space}, depends on the number of available commercial pipe sizes, $N_{com\text{-}pipes}$, and the number of pipes of the network, N_p; therefore, the small networks have a low algorithm efficiency, η_{gen}, and it increases with the decrease of the number of generations or the increase of the total solution space, N_{space}.

The optimization algorithm speed can be evaluated by the number of hydraulic simulations needed before the optimal solution is found. The literature review on WDN optimization focuses on the value of the minimum number of objective function evaluations, $N_{obj\text{-}eval}$ ($N_{obj\text{-}eval} \leq N_{gen}$) at which the best solution is found. Similar to Eq. (3), the influence of the minimum number of objective function evaluations is presented by the evaluation efficiency, η_{eval}, defined herein as:

$$\text{Evaluation Efficiency} = \eta_{eval} = 1 - \frac{\log_{10} N_{obj\text{-}eval}}{\log_{10} N_{space}} \tag{7}$$

In addition, a similar definition can be written for the iteration efficiency, η_{iter}, as a function of the iteration number, N_{iter} ($1 \leq N_{iter} \leq N_{gen}$):

$$\text{Iteration Efficiency} = \eta_{iter} = 1 - \frac{\log_{10} N_{iter}}{\log_{10} N_{space}} \tag{8}$$

The three proposed definitions of η_{gen}, η_{eval}, and η_{iter} in Eqs. (3), (7), and (8), respectively, are based on the particular impacts of N_{gen}, $N_{obj\text{-}eval}$, and N_{iter} referred to the total solution space which is constant for the specified network. These equations satisfy the two extreme conditions. For Eq. (3), the first condition is the ideal efficiency (η_{gen} = 1), which is a generally rare case, when N_{gen} = 1. The second condition is the null efficiency (η_{gen} = 0), when $N_{gen} = N_{space}$. In addition to the satisfied conditions, the mathematical formulation of Eqs. (3), (7), and (8) considers that for large water distribution networks, the value of N_{space}, Eq. (5), is very high and the common logarithm with base ten simplifies the relationship with each of N_{gen}, $N_{obj\text{-}eval}$, and N_{iter} and diminishes the floating point errors.

The speed of optimization algorithm is measured as the ratio of $N_{gen}/N_{obj\text{-}eval}$. However, this ratio is modified according to Eqs. (3) and (7) and the new relationship yields:

$$\frac{\log_{10} N_{gen}}{\log_{10} N_{obj\text{-}eval}} = \frac{1 - \eta_{gen}}{1 - \eta_{eval}} \tag{9}$$

The effect of the population size, N_{search}, and calibration of the control parameters on the efficiency of evolutionary algorithms are not considered mathematically in the present study, but it is investigated in Mora-Melià et al. [18].

The complexity of the optimization of a WDS is related to the size of the total solution space, N_{space}, and the number of local minima near the optimum solution. Therefore, the metaheuristic process is more complex with greater numbers of local minima (Mora-Melia et al. [81]).

The thorough examination of the efficiency of the optimization algorithm demonstrates that the use of the N_{space} and the common logarithm with base ten have a premium importance as they make the value of efficiency varies from 0 to 1.

A visualized interpretation of the different previous performance metrics is shown in Fig. 1. That figure displays a virtual example of the network cost (i.e., effectiveness) for the two-loop network (explained in Section 5) and the computational cost (i.e., efficiency). The two-loop network has a total solution space $N_{space} = 14^8 = 1.475 \times 10^9$ solutions and the proposed values of N_{gen} and $N_{obj\text{-}eval}$ are 20,000 and 2,500, respectively. The figure shows the proposed evolution of the network cost with the number of function evaluations and the network cost at N_{iter} = 1 is taken as $C_{max} = 4.4 \times 10^6$ monetary units. The optimal cost C_{opt} = 419,000 monetary units which is found at $N_{obj\text{-}eval}$ and it remains constant till N_{gen}. On the other hand, the computational cost has a linear increase with the number of iterations, N, and is given the same values of N for simplicity.

Fig. 2 illustrates the corresponding efficiencies of the network cost and the computational cost. For the efficiency, which is plotted in the range ($1 \leq N_{iter} \leq N_{gen}$), Eq. (8), the three definitions of η as a function of $\log_{10} N$, where N takes the value of the number of iterations, evaluations, and generations. The three points $N = N_{iter}$ (=50), $N = N_{obj\text{-}eval}$ (=2,500), and $N = N_{gen}$ (=20,000) and their

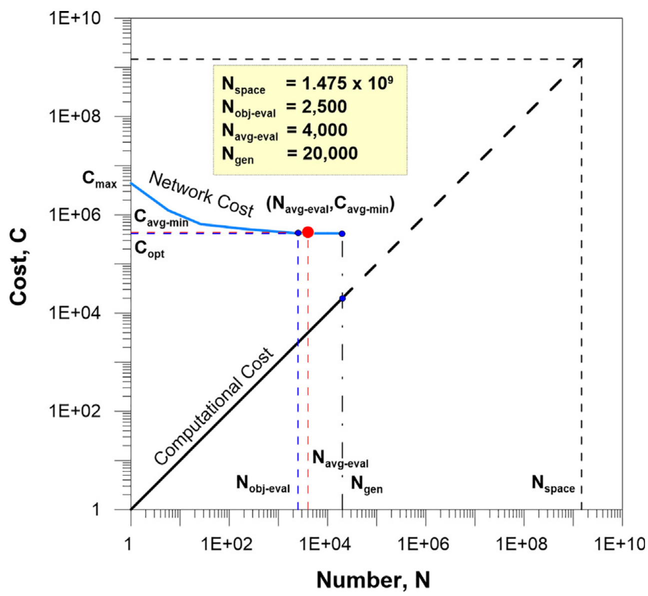

Fig. 1. Evolution of network cost and computational cost for optimization algorithm.

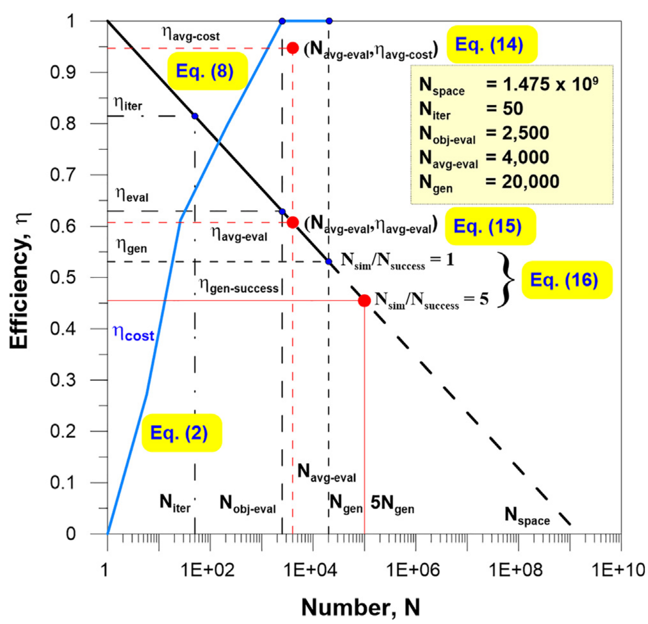

Fig. 2. Effectiveness-efficiency-reliability relationship of optimization algorithm.

corresponding efficiencies, η_{iter} (Eq. (8)), η_{eval} (Eq. (7)), and η_{gen} (Eq. (3)), respectively, are presented in the figure with the condition $\eta_{gen} \leq \eta_{eval}$. For the effectiveness, the variation of η_{cost}, Eq. (2), with N_{iter} increases from 0 till it takes its maximum value of 1 at $N_{obj\text{-}eval}$ and stays constant to the end of number of generations, N_{gen}.

4.3. Reliability

The reliability (robustness) of an optimization algorithm is its ability to find the same optimal solution by varying the control parameter settings (e.g., random seed). It can be evaluated by the number of successes in finding the global minimum, or at least approaching it sufficiently closely (Solomatine [78]). It is indicated by the success efficiency, $\eta_{success}$, which is the ratio of the number of achievements of optimal (or good) cost, $N_{success}$, to the total number of simulations (initiated with different random seeds) performed in the calculations, N_{sim} (Mora-Melia et al. [16]):

$$\text{Reliability} = \eta_{success} = \frac{N_{success}}{N_{sim}} \tag{10}$$

The reliability is a general indicator of algorithm performance; however, varying the total number of simulations of the algorithms, the reliability is not accurately comparable because a larger number of repeated simulations may alter the success rate response (Moosavian and Lence [36]).

4.4. Algorithm performance

The general literature review on the algorithm performance reveals that researchers consider two metrics for its evaluation, namely, the closeness of solutions to the lower cost solution and the quick finding of this solution. For population-based algorithms, their runs identify different solutions. Therefore, it is needed to develop objective methods for the comparison of different algorithms. However, Marchi et al. [82] notify that it is not sufficient to consider only the best result and the minimum number of function evaluations in a run, because the neutrality of the evaluation may be compromised. Although the need for such methodology is evident, few attempts are made by Mora-Melia et al. [16], El-Ghandour and Elbeltagi [19], and Ezzeldin and Djebedjian [61]. It is worth mentioning that Mora-Melia et al. [16] defined the efficiency of the algorithm as the ratio of the success rate $\eta_{success}$ to $\eta_{convergence}$ ($\eta_{convergence}$ = $N_{obj\text{-}eval}$), and applied their equation in Mora-Melia et al. [16,18]. El-Ghandour and Elbeltagi [19] defined the efficiency as the ratio of the success rate $\eta_{success}$ to $\eta_{convergence}$ ($\eta_{convergence}$ = $N_{obj\text{-}eval}/N_{space}$) multiplied by f_c which is an arbitrary constant corresponding to each benchmark network. Ezzeldin and Djebedjian [61] gave the percentage of algorithm efficiency in the case of a single run (i.e., $\eta_{success}$ = 1) as: $\eta_{algorithm}$ = 100 – [0.99 log N_{gen} + 0.01 log(N_{gen} – $N_{obj\text{-}eval}$ + 1)} %. Kavetski et al. [80] used the confidence level for ranking the optimization algorithms in the presence of trade-offs between reliability and computational cost. They defined three characteristic metrics for an algorithm, namely, the characteristic effort (equals to the number of invocations M required to find the desired optimum with a prescribed confidence level), characteristic cost (equals $M.N_{gen}$), and characteristic efficiency (equals $1/(M.N_{gen})$). Lee et al. [83] used the improvement ratio (C_{min}/C_{worst}, C_{worst} is the known worst solution cost) for the comparison of metaheuristic algorithms performance considering a WDN with changeable design characteristics and unknown global optimal solution.

The general accepted fact on the optimization algorithms is that there are some algorithms with high efficiency, but with low reliability in comparison with other optimization algorithms. A general mathematical formulation for the optimization algorithm performance, including the three metrics; effectiveness, efficiency, and reliability, is difficult owing to the fact that an optimization algorithm which always finds the optimal cost (η_{cost} = 1) may have less efficiency than an optimization algorithm which rarely finds the optimal cost, but has high efficiency as it is much faster per run (Kavetski et al. [80]; Chicco and Mazza [23]).

To generate a suitable general performance metrics the following steps were adopted: (1) only algorithms reached optimal solutions are considered, i.e. η_{cost} = 1; (2) the two major factors overwhelm the proposed metrics are the total computational cost, and then the reliability of the algorithm in finding the optimal solution in case of several runs; (3) the two minor factors that distinguish between algorithms, have the same total computational cost and degree of reliability, are speed of convergence to the minimum solution and average deviation (degree of error) of minimum solutions from the optimal one; (4) the input data may be transformed or rescaled, to get more sensitive metrics; and (5) Based on the realm of the researchers judgments the most appropriate forms for the metrics are suggested with several trials and comparisons to satisfy the previous conditions and create noticeable performance differences for different algorithms.

The metrics suggested in the present study to indicate the global performance including the output performance metrics, which are the cost efficiency, η_{cost}, (effectiveness) and the evaluation efficiency, η_{eval}, whereas the input performance metric is the generation efficiency, η_{gen}, (efficiency). The last metric, which has input parameter N_{sim} and output result $N_{success}$, is the success efficiency, $\eta_{success}$, (reliability).

In addition, for some studied WDNs, the interest may be on the effectiveness and efficiency of the optimization algorithm while the reliability may be neglected (i.e., single run is performed). In the case of disregarding the reliability, and for several equal best costs obtained by the optimization algorithm, the best η_{cost} with the minimum N_{gen} (i.e., maximum η_{gen}) and minimum $N_{obj\text{-}eval}$ give the best performance of the algorithm.

The previous discussion of the algorithm performance may lead to the suggestion of two global performance metrics according to two categories of proposed metrics: one for the minimum corresponding values ($N_{obj\text{-}eval}$ and C_{opt}) of several trials/runs, and the second for the average values ($N_{avg\text{-}eval}$ and $C_{avg\text{-}min}$) of multiple runs, as:

(a) Best Global Performance: This proposed metric uses the best effectiveness η_{cost} = 1, the generation efficiency η_{gen} and evaluation efficiency η_{eval}. The success efficiency equals 1 as it is for a single run and that performance metric is only applied on optimal solution results. The proposed global algorithm efficiency is given as optimal cost:

$$\text{Global Algorithm Efficiency} = \eta_{algorithm} = Int(\eta_{cost}) \cdot \left[0.005(1 + \eta_{eval}) + 0.99\,\eta_{gen}\right] \tag{11}$$

$$0.005(1 + \eta_{eval}) \leqslant \eta_{algorithm} \leqslant 1 \tag{12}$$

where Int = Integer of number and it is used to indicate the success (η_{cost} = 1) or failure (η_{cost} < 1) of an algorithm to find the optimal cost. It enforces the global algorithm efficiency to be zero when the effectiveness η_{cost} is < 1.

The proposed definition of the global algorithm efficiency in Eq. (11) is a trade-off for the effects of η_{gen} and η_{eval} and makes the importance of η_{gen} is over η_{eval}. In other words, Eq. (11) keeps the priority of η_{gen} over η_{eval} by making the ranking of η_{gen} more important than the ranking of η_{eval}. The expression of $\eta_{algorithm}$ gives higher value for an optimization algorithm with low N_{gen} (i.e., high η_{gen}) and high $N_{obj\text{-}eval}$ (i.e., low η_{eval}) than for an algorithm with high N_{gen} and low $N_{obj\text{-}eval}$.

The two extreme values of the global algorithm efficiency are defined in Eq. (12). The minimum value corresponds to the condition when the number of generations equals the total solution space (N_{gen} = N_{space}); therefore, η_{gen} = 0, Eq. (3), and $\eta_{algorithm}$ = 0.005(1 + η_{eval}). The maximum value of minimum $\eta_{algorithm}$ is 0.01 when η_{eval} = 1 (i.e., when $N_{obj\text{-}eval}$ = 1), whereas the minimum value of minimum $\eta_{algorithm}$ is 0.005 when η_{eval} = 0 (i.e., when $N_{obj\text{-}eval}$ = N_{space}). The maximum global algorithm efficiency $\eta_{algorithm}$ = 1, Eq. (12), is obtained when the η_{gen} = η_{eval} = 1 (i.e., N_{gen} = $N_{obj\text{-}eval}$ = 1).

The global algorithm efficiency depends on both the WDN under optimization and the parameters of the optimization algorithm (e.g., Simpson et al. [84]; Abdel-Gawad [85]; Zecchin et al. [86]; Ayad et al. [87]; Lee et al. [83]). Therefore, for a specific water distribution network, the calibration ranges of these parameters, which maximize the $\eta_{algorithm}$, are essential. Taking the parameters calibration cost into consideration in the proposed equations is beyond the present study.

(b) Average Global Performance: This method uses the average cost, $C_{avg\text{-}min}$, and its average effectiveness, $\eta_{avg\text{-}cost}$, Eq. (14), the average minimum function evaluations to find the best solutions, $N_{avg\text{-}eval}$, and its corresponding average evaluation efficiency, $\eta_{avg\text{-}eval}$, Eq. (15), and the generation-success efficiency, $\eta_{gen\text{-}success}$, Eq. (16), to define the average global algorithm efficiency, Eq. (13).

The dependence of the reliability, $\eta_{success}$, on the generation efficiency, η_{gen}, is evident in optimization. Increasing the number of generations, N_{gen}, leads to an increase in the search of optimal cost and consequently, an increase in the number of achievements of optimal cost, $N_{success}$. Therefore, the η_{gen}. $\eta_{success}$ is not practically applied and the present study essays the merging of the two metrics by using the multiplication of N_{gen} by ($N_{sim}/N_{success}$) as the trade-off between the efficiency and reliability (Kavetski et al. [80]). The previous multiplication gives the total computational cost to obtain the optimal cost once. The ratio ($N_{sim}/N_{success}$) represents the required number of simulations to find the optimal cost. Furthermore, using the total solution space in the optimization process, N_{gen} = N_{space}, normally gives $\eta_{success}$ = 1 ($N_{sim}/N_{success}$ = 1). Consequently, the proposed generation-success efficiency, Eq. (16), includes the previous efficiency and reliability metrics, and yields the generation efficiency, Eq. (3), when $\eta_{success}$ = 1 ($N_{sim}/N_{success}$ = 1).

$$\text{Average Global Algorithm Efficiency} = \eta_{avg\text{-}algorithm} = Int(\eta_{cost}) \left[0.005 \left(\eta_{avg\text{-}cost} + \eta_{avg\text{-}eval}\right) + 0.99\,\eta_{gen\text{-}success}\right] \tag{13}$$

with

$$\text{Average Effectiveness} = \eta_{avg\text{-}cost} = \frac{C_{opt}}{C_{avg\text{-}min}} \cdot \frac{C_{max} - C_{avg\text{-}min}}{C_{max} - C_{opt}} \tag{14}$$

$$\text{Average Evaluation Efficiency} = \eta_{avg\text{-}eval} = 1 - \frac{\log_{10}\,N_{avg\text{-}eval}}{\log_{10}\,N_{space}} \tag{15}$$

$$\text{Generation} - \text{Success Efficiency} = \eta_{gen-success} = 1 - \frac{log_{10}\,\left[N_{gen} \cdot (N_{sim}/N_{success})\right]}{log_{10}\,N_{space}} = 1 - \frac{\log_{10}(N_{gen}/\eta_{success})}{\log_{10}\,N_{space}} = \eta_{gen} + \frac{\log_{10}(\eta_{success})}{\log_{10}\,N_{space}} \tag{16}$$

The formulation of the global algorithm efficiency, Eq. (11), is derived mathematically from the average global algorithm efficiency, Eq. (13), under the following conditions. If $\eta_{success}$ = 1, then: (1) $\eta_{gen\text{-}success}$ = η_{gen}, Eq. (16), and (2) $\eta_{avg\text{-}cost}$ = 1, Eq. (14), because $C_{avg\text{-}min}$ = C_{opt}. Additionally, if $\eta_{avg\text{-}eval}$ = η_{eval}, then: $\eta_{algorithm}$ = $\eta_{avg\text{-}algorithm}$. Substituting these values in Eq. (13) yields the given Eq. (11). Therefore, for any optimization algorithm, the global algorithm efficiency is superior or equal to the average global algorithm efficiency, $\eta_{algorithm} \geq \eta_{avg\text{-}algorithm}$.

Global performance metric depends on the results of the best at all runs; consequently, the average global performance metric for the same algorithm is always has a lower value. The two metrics are equivalent only in case of all runs behave exactly as the best one; i.e. $\eta_{avg\text{-}cost}$ = 1, $\eta_{avg\text{-}eval}$ = η_{eval}, and $\eta_{success}$ = 1. A great percentage; i.e. 99%, is attached to η_{gen}, Eq. (11), or $\eta_{gen\text{-}success}$, Eq. (13), in versus to only 0.5% for both of η_{eval}, Eq. (11), or $\eta_{avg\text{-}eval}$ and

$\eta_{avg\text{-}cost}$, Eq. (13), to assure satisfying the adopted roles in suggesting the proposed metrics. The great discrepancy between the percentage factors prevent the conflict behavior of the global metrics for two algorithms with $\eta_{gen1} > \eta_{gen2}$, while $\eta_{eval1} < \eta_{eval2}$.

The preceding Fig. 1 shows the average cost, $C_{avg\text{-}min}$, ($C_{avg\text{-}min} \geq C_{opt}$) and the average function evaluations, $N_{avg\text{-}eval}$, ($N_{avg\text{-}eval} \geq N_{obj\text{-}eval}$) obtained for multiple runs. The values of $N_{avg\text{-}eval}$ and $C_{avg\text{-}min}$ are taken as 4,000 and 440,000 monetary units, respectively.

The foregoing Fig. 2 demonstrates the two metrics used for the evaluation of the global algorithm efficiency, Eq. (11); i.e. η_{eval} and η_{gen}. The estimated $\eta_{algorithm}$ is 0.5337 which is slightly greater than η_{gen} (0.5309). In the figure, the dashed line in the range ($N_{gen} \leq N \leq N_{space}$) is the extension of Eq. (8) and it is used for the presentation of the generation-success efficiency, Eq. (16). For multiple runs, there are three red point plots in the figure that characterizes the average global algorithm efficiency, Eq. (13). The first one is the average minimum function evaluations, $N_{avg\text{-}eval}$ (=4,000), and the corresponding average effectiveness, $\eta_{avg\text{-}cost}$, Eq. (14), ($\eta_{avg\text{-}cost} \leq 1$). The second red point plot is the $N_{avg\text{-}eval}$ and the corresponding average effectiveness, $\eta_{avg\text{-}eval}$, Eq. (15), ($\eta_{avg\text{-}eval} \leq \eta_{eval}$). Finally, the third red point plot depends on both the number of generations, N_{gen}, and the inverse of reliability ($1/\eta_{success} = N_{sim}/N_{success}$) to estimate its number N value and the corresponding generation-success efficiency, $\eta_{gen\text{-}success}$, Eq. (16), ($\eta_{gen\text{-}success} \leq \eta_{gen}$). In the figure, the assumed reliability is $\eta_{success}$ = 20%; therefore, $N_{gen}/\eta_{success}$ = 5 N_{gen}. The average global algorithm efficiency determined by Eq. (13) using the three previous efficiencies gives $\eta_{avg\text{-}algorithm}$ = 0.4582. It is higher slightly from the generation-success efficiency, $\eta_{gen\text{-}success}$ = 0.4555.

5. Benchmark networks

Several benchmark WDNs are available (Giudicianni et al. [88]). Wang et al. [89] and Poojitha et al. [35] classified water distribution system design basing on the search space size into four categories: small, medium, intermediate, and large network problems. In the present study, three benchmark networks are used; namely, the two-loop network (Alperovits and Shamir [90]), the Hanoi network (Fujiwara and Khang [91]), and the New York tunnels network (Schaake and Lai [92]). According to the classification of Wang et al. [89], the two-loop network is a small network, and the Hanoi water distribution network and New York tunnels network are medium networks. In addition, the topology of typical water systems is classified as real and synthetic WDNs, Giudicianni et al. [88]. The three networks are synthetic networks. Finally, Moosavian and Lence [20] defined the degree of candidate diameter, which is an indicator of the size and complexity of the network problem, and it is the ratio of the number of candidate diameters to the number of pipes.

The two-loop network, Fig. 3(a), is a network fed by a reservoir with 210 m constant head. All pipes have fixed length of 1000 m. The demands and other data are widely reported in many previous studies (e.g., Alperovits and Shamir [90]; Quindry et al. [93]).

The Hanoi WDN (Vietnam), Fig. 3(b), which is fed by a single reservoir of 100 m constant head, is the second benchmark network used in the present study. Additional data on the network are given in previous works (Fujiwara and Khang [91]; Savic and Walters [94]).

The New York City tunnels system (USA), Fig. 3(c), is the third case study. It is a flow system and for which water is drawn from a single source. A parallel expansion is required as the water demands at the 20 nodes are not satisfied. The installation of new pipes parallel to the existing 21 tunnels necessitates the expansion cost optimization by obtaining the optimal diameter of the new pipes. Table 2 gives the details of the three networks and optimization data, whereas Table 3 gives the available pipe diameters and the corresponding cost for the three case studies.

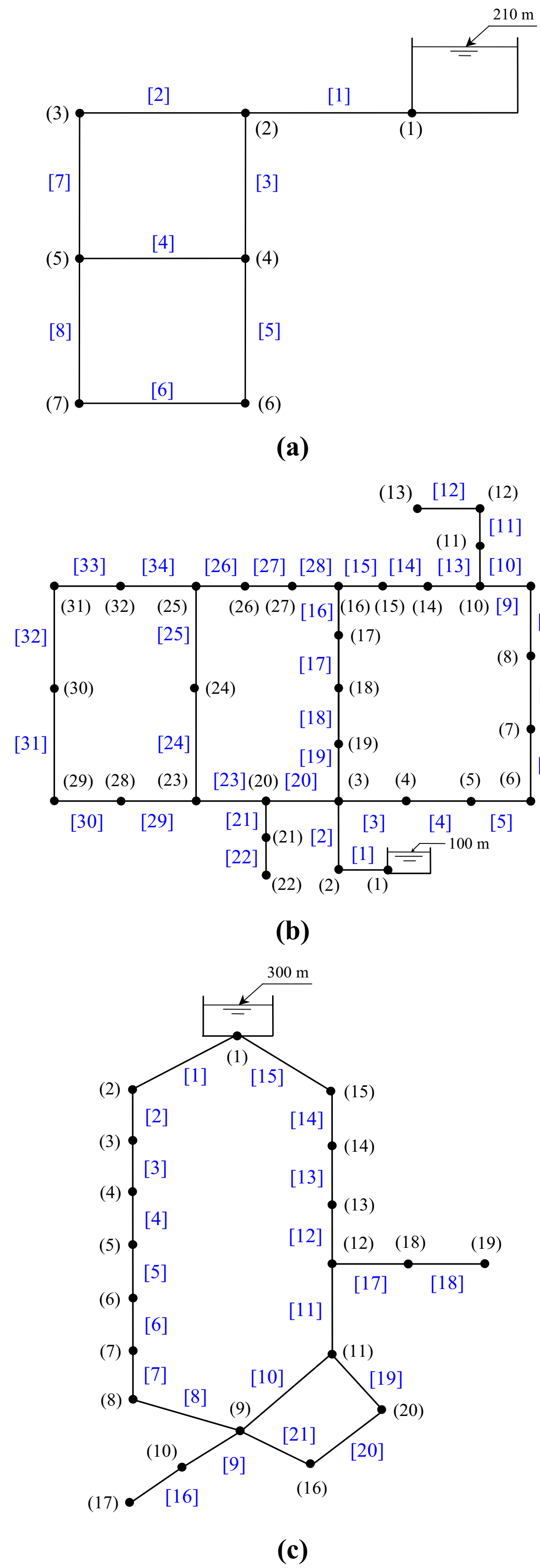

Fig. 3. Layout of three benchmark networks: (a) Two-loop network; (b) Hanoi network; and (c) New York tunnels network.

Table 2
Case studies data and optimization requirements.

Case study	Network data				Optimization			
	No. of Pipes, N_p	No. of nodes	No. of reservoirs	No. of loops	Hazen-Williams coefficient, C	No. of available diameters (Range)	Search space size, N_{space}	Degree of candidate diameter	Pressure head constraint
Two-loop	8	7	1	2	130	14 (1″ – 24″)	$14^8 = 1.48 \times 10^9$	14/8 = 1.75	30 *m*
Hanoi	34	32	1	3	130	6 (12″ – 40″)	$6^{34} = 2.865 \times 10^{26}$	6/34 = 0.1765	30 *m*
New York	21	20	1	2	100	16 (0″ – 204″) 0″ = No pipe	$16^{21} = 1.934 \times 10^{25}$	16/21 = 0.7619	255 ft (260 ft in node 16, 272.8 ft in node 17)

The least cost optimization problem for pipe networks can be formulated according to Djebedjian et al. [62]. The head loss due to friction in a pipe, h_f, is expressed by the Hazen-Williams formula:

$$h_f = \frac{\omega}{C_i^{\alpha}} \frac{L_i \, q_i^{\alpha}}{D_i^{\beta}} \tag{17}$$

where L_i = length of pipe i; q_i = flow in pipe i; D_i = diameter of pipe i; ω = conversion factor which accounts for the system of units used; and α and β = exponents. Different values for ω, α, and β have been used in the literature, but only the corresponding values adopted by the hydraulic solver EPANET 2 (Rossman [95]) are used here with the following magnitudes ω = 10.667, α = 1.852, and β = 4.871 for q_i in m^3/s and D_i and L_i in m; and C_i = Hazen-Williams roughness coefficient for pipe *i*. Whereas for English units, ω = 4.7279 for q_i in cfs and D_i and L_i in ft.

6. Results and discussion

The quality evaluation of the optimal design of water distribution network depends on the investment costs with a restricted fulfillment of the minimum nodal pressure head constraints.

The water distribution network design can be categorized optimization-wise as: (a) split-pipe design (i.e., pipes have one or two fixed diameter segments), (e.g., Alperovits and Shamir [90]) and practically this solution is unrealistic; (b) continuous diameter design (diameter is taken to be a continuous variable using nonlinear programming (e.g., Fujiwara and Khang [91]), and it is not practical as certain diameter sizes are marketed; and (c) discrete diameter design uses diameter sets available commercially. In the light of these categories, it is obvious that pipe diameters have to be considered as discrete variables in the optimization algorithms.

The uncertainty associated with the Hazen-Williams equation numerical conversion constant ω arises different optimal solutions for the same network. In the literature, six common values are used (ω = 10.4516, 10.5088, 10.5879, 10.667, 10.674, and 10.9031). Greater value of ω increases the head loss in the pipe and violates the requirements for minimum pressure. As a result, the network needs larger diameter for delivering the specified amount of water and requires a more costly WDN design. Consequently, the recent researchers only adopted the common value ω = 10.667 used in the EPANET 2 software (Rossman [95]).

The three case studies optimization results (optimal diameters) are given in Table 4. Related comparison tables for the data of optimization results of these networks can be found in Suribabu [32], Zheng et al. [96,51]), Sadollah et al. [46], Sheikholeslami et al. [30], Delir et al. [66], Moosavian and Lence [36], and Ezzeldin and Djebedjian [61].

6.1. Two-loop network

The optimal cost for the two-loop network, C_{opt}, is 419,000 monetary units and it is obtained by most researches as given in Table 5. In the table, the authors' names are arranged in alphabetical order according to the publication year. It is worth mentioning that researches using conversion constant different than ω = 10.667 or 10.674 are not mentioned in the table (e.g., Alperovits and Shamir [90]; Goulter et al. [110]; Kessler and Shamir [111]; Savic and Walters [94]; Cunha and Sousa [112]; Wu et al. [113]; Geem [114]; Afshar [115]; Zhou et al. [57]).

The performance evaluation methodology is applied to measure the global performance of different metaheuristic optimization algorithms and the results are given in Table 5. It gives the total number of evaluations (N_{gen}), minimum number of function evaluations to reach the optimal cost ($N_{obj\text{-}eval}$), average function evalu-

Table 3
Cost of available pipe diameters for the case studies.

Two-Loop Network		Hanoi Network		New York Tunnels	
Available Diameters (in.)	Cost (Units/m)	Available Diameters (in.)	Cost ($/m)	Available Diameters (in.)	Cost ($/ft)
1	2	12	45.726	0[a]	0[a]
2	5	16	70.40	36	93.5
3	8	20	98.378	48	134
4	11	24	129.333	60	176
6	16	30	180.748	72	221
8	23	40	278.28	84	267
10	32	–	–	96	316
12	50	–	–	108	365
14	60	–	–	120	417
16	90	–	–	132	469
18	130	–	–	144	522
20	170	–	–	156	577
22	300	–	–	168	632
24	550	–	–	180	689
–	–	–	–	192	746
–	–	–	–	204	804

Equivalent diameter: inches (meter) – 1″ (0.0254), 4″ (0.1016), 10″ (0.2540), 12″ (0.3048), 16″ (0.4064), 18″ (0.4572), 20″ (0.508), 24″ (0.6096), 30″ (0.762), 36″ (0.9144), 40″ (1.016), 48″ (1.2192), 60″ (1.524), 72″ (1.8288), 84″ (2.1336), 96″ (2.4384), 108″ (2.7432), 120″ (3.048), 132″ (3.3528), 144″ (3.6576), 156″ (3.9624), 168″ (4.2672), 180″ (4.572), 192″ (4.8768), 204″ (5.1816).
[a] do-nothing option

Table 4
Optimal pipe diameters for the case studies.

Two-Loop Network		Hanoi Network				New York Tunnels	
Pipe	Diameter (in.)	Pipes	Diameter (in.)	Pipes	Diameter (in.)	Pipes	Diameter (in.)
1	18	1–9	40	21	20	1–6	0
2	10	10	30	22	12	7	144
3	16	11–12	24	23	40	8–15	0
4	4	13	20	24–25	30	16–17	96
5	16	14	16	26	20	18	84
6	10	15–16	12	27–28	12	19	72
7	10	17	16	29	16	20	0
8	1	18	24	30–31	12	21	72
–	–	19	20	32–33	16	–	–
–	–	20	40	34	24	–	–

ation number ($N_{avg\text{-}eval}$), average minimum cost ($C_{avg\text{-}min}$), generation efficiency (η_{gen}, Eq. (3)), evaluation efficiency (η_{eval}, Eq. (7)), success efficiency ($\eta_{success}$, Eq. (10)), global algorithm efficiency ($\eta_{algorithm}$, Eq. (11)), and average global algorithm efficiency ($\eta_{avg\text{-}algorithm}$, Eq. (13)). The values of N_{gen} and $N_{obj\text{-}eval}$ that are not given in the table are due to the source literature. Similarly, the number of runs that has achieved the best solution in some researches are not mentioned; consequently, the corresponding reliability is not calculated in the table. Although the reliability of different algorithms is not based on the same number of runs, the comparison may be nominal between different EAs as they use the same total number of generations, N_{gen}, Moosavian and Lence [36].

Literature data that reached optimal solutions are only considered in the present paper; i.e. η_{cost} = 1. Consequently, discrepancies between different algorithms are manifested by the remaining metrics, Table 5.

The best generation efficiency of various optimization algorithms is the micro-Genetic algorithm (μGA) of Djebedjian et al. [99], (η_{gen} = 68.7%). In view of the evaluation efficiency, the SBA of Shende and Chau [52] has the maximum evaluation efficiency with η_{eval} = 78.2%. On the other hand, the reliability of the used optimization algorithms reveals that the five algorithms PSO of Suribabu and Neelakantan [100], SS of Lin et al. [56], MA of Baños et al. [47], PSO-DE of Sedki and Ouazar [74], and DE of Poojitha et al. [35] achieve the maximum reliability, $\eta_{success}$ = 100%.

The minimum number of function evaluations, $N_{obj\text{-}eval}$, to optimal solution are 100, 197, 204, 549, and 741 which are reached by algorithms SBA, FDE, PSHS, IDPSO, and μGA, respectively.

Best global performance for one run, $\eta_{algorithm}$, is reached by μGA (N_{gen} = 744) with magnitude 68.68%. The second competitive algorithm is FDE (Moosavian and Lence [36]) with $N_{gen} = 10^3$ and $\eta_{algorithm}$ = 67.483%, but if the latter algorithm is adopted N_{gen} just > $N_{obj\text{-}eval}$ = 197, as the μGA did, it will reach a more efficient global performance than it.

Increasing N_{gen} from 10^3 to 5×10^3 increases the FDE reliability progressively from 45% to 86%, but further increasing of N_{gen} has a lesser effect. PSO-DE reached the optimal cost every run, with $N_{gen} = 7 \times 10^3$ and $N_{avg\text{-}eval}$ = 3,080, but the proposed global average performance metric, $\eta_{avg\text{-}algorithm}$, assign a higher performance for the FDE algorithm, 63.711%, due to the following three reasons: (1) $N_{avg\text{-}eval}$ = 600 and 3,080, respectively, for the FDE and the PSO-DE; i.e. FDE converges faster to optimal solution with a lesser $N_{gen} = 10^3$; (2) deviation percentage of $C_{avg\text{-}min}$ is only 0.24% from the optimal solution which is insignificant; and (3) PSO-DE can reach optimal solution every run with number of individual evaluations, $N_{gen} = 7 \times 10^3$, while the FDE can reach the same optimal minimum with a smaller number of individual evaluations, Eq. (16), equal to $N_{gen}/\eta_{success} = 10^3/0.45$ = 2,222.

6.2. Hanoi network

Many researchers used different values for ω other than 10.667 or 10.674 for the optimization of Hanoi network (e.g., Fujiwara and Khang [91]; Savic and Walters [94]; Cunha and Sousa [112]; Geem et al. [43]; Geem [114]; Kadu et al. [116]; Reca et al. [75]; Haghighi

Table 5
Algorithms performance evaluation for the Two-Loop network.

Authors	Algorithm	N_{gen}	Minimum	Average		Performance metrics			Algorithm efficiency	
			$N_{obj\text{-}eval}$	$N_{avg\text{-}eval}$	$C_{avg\text{-}min}$ (UnitsM)	η_{gen} (%)	η_{eval} (%)	$\eta_{success}$ (%)	$\eta_{algorithm}$ (%)	$\eta_{avg\text{-}algorithm}$ (%)
Abebe and Solomatine [97]	GA	–	1,373	–	–	–	65.8	–	–	–
Eusuff and Lansey [54]	SFLA	17,000	11,155	11,323	–	53.9	55.9	–	54.102	–
Liong and Atiquzzaman [53]	SCE	–	1,019	1,345	–	–	67.2	50	–	–
Prasad and Park [98]	GA	–	100,000	–	–	–	45.5	–	–	–
Afshar and Mariño [29]	cGA	10,000	4,600	–	–	56.4	60.1	–	56.611	–
Djebedjian et al. [99]	μGA	744	741	–	–	68.7	68.7	–	68.838	–
Neelakantan and Suribabu [38]	GA_{mod}	–	2,440	–	–	–	63.1	–	–	–
Reca and Martínez [39]	GENOME	150,000	< 10,000	–	–	43.5	–	50	–	–
Suribabu and Neelakantan [100]	PSO	7,650	1,875	5,138	0.419	57.6	64.3	100	57.889	57.865
Suribabu and Neelakantan [49]	PSO	2,000	760	–	–	64.0	68.6	–	64.201	–
Lin et al. [56]	SS	11,490	–	3,215	0.419	55.7	–	100	–	55.969
Perelman and Ostfeld [27]	CE	35,840	35,000	–	–	50.3	50.4	–	50.578	–
Afshar [101]	cGA	10,000	3,000	–	–	56.4	62.1	–	56.621	–
Geem [73]	PSHS	5,000	204	233	–	59.7	74.8	13	59.935	–
Baños et al. [47]	MA	9,161	$\approx$ 8,100	–	0.419	56.8	57.4	100	57.009	–
Bolognesi et al. [40]	GHEST	25,000	1,350	3,625	0.433	52.0	65.9	30	52.344	46.657
Mohan and Babu [42]	HBMO	–	1,293	–	–	–	66.1	–	–	–
Suribabu [32]	DE	10,000	1,320	4,750	–	56.4	66.0	40	56.641	–
Chandramouli and Malleswararao [102]	GA	–	800	–	–	–	68.3	–	–	–
Dong et al. [103]	DE	10,000	–	5,987	0.424	56.4	–	40	–	52.302
Dong et al. [103]	GA	10,000	–	5,739	0.471	56.4	–	3	–	40.102
Sedki and Ouazar [74]	PSO	6,000	–	3,120	0.423	58.8	–	–	–	–
Sedki and Ouazar [74]	PSO-DE	7,000	–	3,080	0.419	58.1	–	100	–	58.293
Babu and Vijayalakshmi [104]	PSO-GA	5,000	1,300	–	–	59.7	66.0	–	59.892	–
Ezzeldin et al. [44]	IDPSO	5,000	549	–	–	59.7	70.1	–	59.912	–
Moosavian and Roodsari [55]	SLC	5,000	968	2,051	–	59.7	67.4	40	59.899	–
Uma [105]	DE	10,000	5,300	–	–	56.4	59.4	–	56.608	–
Reca et al. [26]	B-GA	20,000	2,000	–	–	53.1	64.0	30	53.381	–
El-Ghandour and Elbeltagi [19]	GA	20,000	6,060	–	0.438	53.1	58.7	4	53.355	–
El-Ghandour and Elbeltagi [19]	PSO	2,500	1,650	–	0.430	62.9	64.9	24	63.136	–
El-Ghandour and Elbeltagi [19]	ACO	25,000	2,650	–	0.435	52.0	62.7	14	52.328	–
El-Ghandour and Elbeltagi [19]	MA	20,000	11,402	–	0.425	53.1	55.8	32	53.340	–
El-Ghandour and Elbeltagi [19]	SFLA	14,000	6,921	–	0.426	54.8	58.1	22	55.024	–
Moeini and Moulaei [106]	ACOA2[a]	100,000	4,700	–	0.422	45.5	60.0	–	45.814	–
Surco et al. [107]	$PSO_{modified}$	1,650	1,650	–	–	64.9	64.9	–	65.085	–
Abdy Sayyed et al. [108]	GA	4,000	1,000	–	–	60.7	67.3	–	60.944	–
Moosavian and Lence [36]	FDE	1,000	197	600	0.420	67.3	75.0	45	67.483	63.711
Moosavian and Lence [36]	FDE	5,000	197	1,116	0.419	59.7	75.0	86	59.936	59.188
Moosavian and Lence [36]	FDE	10,000	197	1,300	0.419	56.4	75.0	88	56.686	56.042
Moosavian and Lence [36]	FDE	100,000	197	4,172	0.419	45.5	75.0	99	45.889	45.769
Praneeth et al. [109]	WCA	22,000	2,200	–	–	52.6	63.5	–	52.932	–
Shende and Chau [52]	SBA	–	100	–	–	–	78.2	–	–	–
Ezzeldin and Djebedjian [61]	WOA	2,100	1,068	–	–	63.8	67.0	–	63.964	–
Poojitha et al. [35]	GA1[b]	40,000	4,200	4,500	–	49.8	60.5	8	50.113	–
Poojitha et al. [35]	EGA1[c]	40,000	7,700	4,900	–	49.8	57.6	22	50.099	–
Poojitha et al. [35]	GA2[d]	40,000	4,300	6,600	–	49.8	60.4	6	50.112	–
Poojitha et al. [35]	EGA2[e]	40,000	5,500	6,500	–	49.8	59.2	10	50.107	–
Poojitha et al. [35]	GA3[f]	40,000	6,400	8,300	–	49.8	58.5	2	50.103	–
Poojitha et al. [35]	EGA3[g]	40,000	3,600	24,000	–	49.8	61.2	4	50.117	–
Poojitha et al. [35]	DE	40,000	7,600	13,500	0.419	49.8	57.7	100	50.099	50.085

Optimal Cost C_{opt} = 0.419 MUnits. Maximum Cost C_{max} = 4.400 MUnits. Cost Efficiency η_{cost} = 100%. Search space $N_{space} = 14^8 = 1.48 \times 10^9$.
[a] ACOA2 = ACOA with Max-Min Ant System (MMAS);
[b] GA1 = GA with truncation;
[c] EGA1 = elitist GA with truncation;
[d] GA2 = GA with tournament;
[e] EGA2 = elitist GA with tournament;
[f] GA3 = GA with roulette-wheel; and
[g] EGA3 = elitist GA with roulette-wheel method of selection.

et al. [69]; Surco et al. [107]). The best optimal cost for the Hanoi network is US $6,081,087 ($\omega$ = 10.667).

The best minimum costs, according the values of ω, are US $6.056 million ($\omega$ = 10.5088, α = 1.85, β = 4.87), (e.g., Wu et al. [113]; Lin et al. [56]; Sung et al. [117]; Kadu et al. [116]; Singh et al. [118]; Zhou et al. [57]) and US $6.183 million ($\omega$ = 10.9031, α = 1.852, β = 4.87), (e.g., Wu et al. [113]; Lin et al. [56]; Sung et al. [117]). Therefore, their results are excluded from the present study. It is worthy mentioning that although Reca and Martínez [39], Surco et al. [107] and Dandy et al. [13], and Poojitha et al. [35] used (ω = 10.674, α = 1.852, β = 4.871), they obtained optimal costs of US $6,081,127, US $6,081,150.91, and US $6,081,118, respectively, due to the approximation of the values of pipe costs used in their studies.

The optimization of Hanoi network using the split-pipe design (e.g., Fujiwara and Khang [91]; Sonak and Bhave [119]; Eiger et al. [120]; Varma et al. [121]; Sherali et al. [122]) and the continuous diameter design (e.g., Fujiwara and Khang [91]; Varma et al. [121]; Ghajarnia et al. [123]) are not mentioned in the present study as it is restricted to the discrete diameter design.

Different optimal results for (ω = 10.667) are presented in Table 6.

The optimization of Hanoi network is relatively quite difficult due to the huge solution space dimensions, N_{space} = 2.87 × 10^{26}; therefore, the N_{gen}'s have higher values than the ones used for the two loop WDN, with a varied range from 10^3 to 5 × 10^5.

Fulfilling the effectiveness condition (i.e., η_{cost} = 100%), the best generation efficiency of various optimization algorithms is the FDE

Table 6
Algorithms performance evaluation for the Hanoi network.

Authors	Algorithm	N_{gen}	Minimum	Average		Performance metrics			Algorithm efficiency	
			$N_{obj-eval}$	$N_{avg-eval}$	$C_{avg-min}$ ($M)	η_{gen} (%)	η_{eval} (%)	$\eta_{success}$ (%)	$\eta_{algorithm}$ (%)	$\eta_{avg-algorithm}$ (%)
Neelakantan and Suribabu [38]	GA	–	1,234,340	–	–	–	77.0	–	–	–
Neelakantan and Suribabu [38]	GA_{mod}	–	74,500	–	–	–	81.6	–	–	–
Geem [124]	HS	50,000	27,721	–	–	82.2	83.2	1.2	82.333	–
Reca and Martínez [39]	GENOME	150,000	–	–	6.248	80.4	–	10	–	–
Suribabu and Neelakantan [49]	PSO	25,000	6,600	–	–	83.4	85.6	–	83.472	–
Lin et al. [56]	SS	60,440	–	43,149	–	81.9	–	64	–	–
Perelman and Ostfeld [27]	CE	97,920	97,000	–	–	81.1	81.2	–	81.231	–
Sung et al. [117]	TS	–	40,200	–	–	–	82.6	30	–	–
Geem [73]	PSHS	50,000	17,980	–	–	82.2	83.9	1.2	82.337	–
Tolson et al. [70]	$PSO_{variant}$	80,000	–	–	6.310	81.5	–	5	–	–
Tolson et al. [70]	HD-DDS	100,000	–	100,000	6.252	81.1	–	8	–	77.078
Bolognesi et al. [40]	GHEST	50,000	30,850	36,735	6.179	82.2	83.0	40	82.333	80.834
Dandy et al. [13]	DE	500,000	–	–	6.301	78.5	–	13.3	–	–
Suribabu [32]	DE[a]	10,000	3,540	6,244	–	84.9	86.6	20.7	84.966	–
Suribabu [32]	DE[b]	100,000	–	48,724	–	81.1	–	82	–	–
Zheng et al. [96]	DE1[c]	300,000	–	74,584	6.088	79.3	–	86	–	79.168
Zheng et al. [96]	DE2[c]	300,000	–	6,660	6.240	79.3	–	4	–	74.190
Zheng et al. [96]	DE3[c]	300,000	–	195,872	6.109	79.3	–	84	–	79.120
Zheng et al. [96]	DE4[c]	300,000	–	189,432	6.100	79.3	–	84	–	79.121
Zheng et al. [72]	NLP-DE1[d]	80,000	–	34,609	6.082	81.5	–	97	–	81.518
Zheng et al. [72]	NLP-DE2[e]	80,000	–	42,782	6.081	81.5	–	98	–	81.533
Dong et al. [103]	DE	100,000	–	31,618	6.081	81.1	–	98	–	81.173
Sedki and Ouazar [74]	PSO-DE	45,000	40,200	–	6.366	82.4	82.6	–	82.502	–
Zheng et al. [14]	SDE	500,000	–	77,220	–	78.5	–	92	–	–
Zheng et al. [14]	DDE	500,000	–	63,700	–	78.5	–	80	–	–
Zheng et al. [51]	SADE	74,876	–	60,532	6.090	81.6	–	84	–	81.387
Aghdam et al. [64]	AMPSO	25,000	–	–	–	83.4	–	–	–	–
Marchi et al. [82]	GA_{trad}	500,000	300,000	–	6.247	78.5	79.3	3.3	78.572	–
Marchi et al. [82]	GA_{mod}	500,000	500,000	–	6.196	78.5	78.5	6.7	78.568	–
Marchi et al. [82]	PSO	500,000	100,000	–	6.253	78.5	81.1	10	78.581	–
Marchi et al. [82]	DE	500,000	300,000	–	6.082	78.5	79.3	96.7	78.572	–
Moosavian and Roodsari [55]	SLC1[f]	100,000	–	29,108	6.110	81.1	–	80	–	80.842
Moosavian and Roodsari [55]	SLC2[g]	100,000	–	71,789	6.081	81.1	–	100	–	81.199
Sheikholeslami et al. [31]	CSS	16,440	16,440	–	–	84.1	84.1	–	84.145	–
Zheng et al. [65]	BLP-DE	40,000	–	33,148	6.085	82.6	–	98	–	82.661
Sadollah et al. [46]	MBA	30,000	22,450	–	6.150	83.1	83.6	–	83.165	–
Sadollah et al. [46]	IMBA	30,000	16,400	–	6.145	83.1	84.1	–	83.168	–
Qi et al. [71]	ISEDPSO	375,000	–	17,600	6.102	78.9	–	93.3	–	78.949
Qi et al. [71]	PEDPSO	250,000	–	23,400	6.103	79.6	–	90	–	79.546
Sheikholeslami and Talatahari [34]	DSO	60,000	28,140	39,280	–	81.9	83.2	–	82.037	–
Sheikholeslami et al. [30]	CS	60,000	52,890	–	6.195	81.9	82.1	–	82.032	–
Sheikholeslami et al. [30]	CSHS	60,000	31,800	–	6.107	81.9	83.0	–	82.036	–
Uma [105]	DE	50,000	28,000	–	–	82.2	83.2	–	82.333	–
Moosavian and Lence [20]	SLC	10,000	–	–	6.300	84.9	–	–	–	–
Moosavian and Lence [20]	GA	40,000	–	–	6.500	82.6	–	–	–	–
Moosavian and Lence [20]	SLC	40,000	–	–	6.200	82.6	–	–	–	–
Surco et al. [107]	$PSO_{modified}$	18,000	14,000	–	–	83.9	84.3	–	83.999	–
Abdy Sayyed et al. [108]	GA	48,000	18,400	–	–	82.3	83.9	–	82.403	–
Delir et al. [66]	Std. CSS	20,000	16,440	–	6.251	83.7	84.1	–	83.827	–
Delir et al. [66]	CSS-FA	20,000	14,600	–	6.217	83.7	84.3	–	83.828	–
Fallah et al. [41]	GSA	7,500	–	6,908	6.129	85.4	–	80	–	85.061
Moosavian and Lence [36]	FDE	1,000	241	528	6.581	88.7	91.0	63	88.730	87.934
Moosavian and Lence [36]	FDE	5,000	241	822	6.120	86.0	91.0	90	86.114	85.930
Moosavian and Lence [36]	FDE	10,000	241	1,146	6.093	84.9	91.0	95	84.988	84.891
Moosavian and Lence [36]	FDE	100,000	241	2,065	6.088	81.1	91.0	97	81.246	81.178
Shende and Chau [52]	SBA	–	600	–	–	–	89.5	–	–	–
Bi et al. [125]	DE	10,000	–	–	6.155	84.9	–	–	–	–
Ezzeldin and Djebedjian [61]	WOA	180,000	113,142	–	–	80.1	80.9	–	80.240	–
Poojitha et al. [35]	DE	150,000	59,400	66,500	–	80.4	82.0	92	80.542	–

Optimal Cost C_{opt} = 6.081 M$. Maximum Cost C_{max} = 10,969,797.6 $. Cost Efficiency η_{cost} = 100%. Search space N_{space} = 6^{34} = 2.87 × 10^{26}.
[a] Population size = 20;
[b] Population size = 100;
[c] Five mutation strategies in DE: DE1-Rand1, DE2-Best1, DE3-Best2, DE4-CurrentToBest2, and DE5-Rand2;
[d] NLP-DE1: DE seeded with two tailored pipe diameters;
[e] NLP-DE2: DE seeded with four tailored pipe diameters;
[f] SLC1 = SLC without relegation and promotion; and
[g] SLC2 = SLC with relegation and promotion.

(N_{gen} = 1,000) of Moosavian and Lence [36], (η_{gen} = 88.7%). Considering the evaluation efficiency, the minimum $N_{obj\text{-}eval}$ values are 241 and 600 for FDE and SBA, respectively. Consequently, the FDE of Moosavian and Lence [36] has the maximum evaluation efficiency with η_{eval} = 91%.

For the reliability, the SLC with relegation and promotion; i.e. the SLC2 (Moosavian and Roodsari [55]), reached the optimal solution with $\eta_{success}$ = 100%, but with expensive computational effort, $N_{gen} = 10^5$ and $N_{avg\text{-}eval}$ = 71,789. Also, the NLP-DE2 (Zheng et al. [72]), DE (Dong et al. [103]), and BLP-DE (Zheng et al. [65]) have high reliability with $\eta_{success}$ = 98%. Surprisingly for the values of the $N_{gen} = 10^3$, 5×10^3, 10^4, and 10^5, FDE has a higher reliability with respect to the two loop WDN, which is an indicator that FDE has a better performance for WDN with medium N_{space}.

Best global performance, $\eta_{algorithm}$ = 88.730%, is obtained from the FDE algorithm with N_{gen} is only equal 10^3. For $N_{gen} \leq 10^4$, the best performed algorithm is the FDE with average global performance, $\eta_{avg\text{-}algorithm}$ = 84.891%, and enhances to 87.934% by considering $N_{gen} = 10^3$. That algorithm catches the minimum expected number of function evaluations to the optimal solution which is equal to $N_{gen}/\eta_{succcess} = 10^3/0.63$ = 1,588.

6.3. New York network

As in the two previous case studies of the two-loop and Hanoi networks, different values for ω other than 10.667 or 10.674 were employed by many researchers for the optimization of New York tunnels network (e.g., Savic and Walters [94]; Cunha and Sousa [112]; Wu et al. [113]; Cunha and Ribeiro [126]; Lin et al. [56]).

The best minimum costs, according to the two extreme values of ω, are US $36.68 million ($\omega$ = 10.5088, α = 1.85, β = 4.87), (e.g., Lin et al. [56]), and US $40.42 million ($\omega$ = 10.9031, α = 1.852, β = 4.87), (e.g., Lin et al. [56]; Sung et al. [117]; Chu et al. [127]).

The fulfillment of pressure constraints is essential and it is worth noting that the solutions of Lippai et al. [58] and Eusuff and Lansey [54] are infeasible because the minimum required pressure head at nodes 17 and 19 is not satisfied when the optimal diameters are simulated by EPANET 2 software (Rossman [95]), (Vasan and Simonovic [128]). Similarly, there are some solutions as US $38.13 million (e.g., Lin et al. [56], ω = 10.667) and US $38.31 million (e.g., Fallah et al. [41], ω = 10.667) are infeasible after evaluating the nodal head constraints by EPANET 2 (Rossman [95]) due to the approximation of conversion factors from English units to the International System of Units (SI).

Table 7 summarizes the previous available results on the optimization of New York network. The best-known minimum cost found by all algorithms for the New York network is C_{opt} = US $38.64 million first reported by Maier et al. [25].

It is worthy noting that an optimal solution of US $38.52 million is obtained using the PSO-DE (Sedki and Ouazar [74]), AMMSFL (Aghdam et al. [63]), AMPSO (Aghdam et al. [64]), and FSSFL (Aghdam et al. [67]). This solution is feasible after evaluating the nodal head constraints, but the minimum pressure head excess of 0.02 ft (0.0061 m) at node 16 which is somehow critical. Therefore, for the suitability of the present study issued for the comparison of optimization algorithms performance, C_{opt} = US $38.64 million is used as it is the most optimum reached in many researches, Table 7.

For the New York WDN, $N_{space} = 1.934 \times 10^{25}$, and N_{gen} is varied between 10^3 and 3×10^5 for the different algorithms, Table 7. The best generation efficiency is the FDE (N_{gen} = 1,000) of Moosavian and Lence [36], (η_{gen} = 88.1%). For the evaluation efficiency, the FDE achieves a high efficiency with η_{eval} = 90.6% because it reached the optimal solution with $N_{obj\text{-}eval}$ = 238, which is far lower than the other algorithms (e.g. CSS with $N_{obj\text{-}eval} = 2 \times 10^3$). Therefore, the FDE has a superior speed to optimal solution with respect to the remaining algorithms.

Four algorithms can reach the optimal solution for any run ($\eta_{success}$ = 100%), which are the GHEST (Bolognesi et al. [40]), SLC2 (Moosavian and Roodsari [55]), BLP-DE (Zheng et al. [65]), and FDE with ($N_{gen} = 5 \times 10^4$, 10^5, 7,500, 10^5) and ($N_{avg\text{-}eval}$ = 7,795, 15,764, 3,486, 4,193), respectively.

The best global algorithm efficiency is achieved by the FDE of Moosavian and Lence [36] (N_{gen} = 1,000) ($\eta_{algorithm}$ = 88.208%) and followed by the CSS (Sheikholeslami et al. [31]) with $\eta_{algorithm}$ = 87.011%.

The best average global algorithm efficiency is reached by the FDE of Moosavian and Lence [36] (N_{gen} = 1,000) ($\eta_{avg\text{-}algorithm}$ = 86.763%). After that, the BLP-DE has the second rank of algorithms with 84.759%. Despite the superior convergence of the BLP-DE to the optimal solution ($\eta_{success}$ = 100%), it has a lower $\eta_{avg\text{-}algorithm}$ with respect to the FDE algorithm with $N_{gen} = 5 \times 10^3$, $N_{avg\text{-}eval}$ = 1,454, and $\eta_{success}$ = 84%. This is due to the reasonable balance between both of the computational cost, N_{gen}, and speed of convergence, $N_{avg\text{-}eval}$, with reliability of success. For the FDE ($N_{gen} = 10^3$), the expected number of individual evaluations to the optimal solution $N_{gen}/\eta_{succcess} = 10^3/0.47$ = 2,128.

7. Conclusions and recommendations

Several conclusions are achieved from analyzing the literature, concerned with finding optimal cost of three well-known WDNs under a restricted satisfaction of prespecified hydraulic heads at different nodes, as: (1) different conversions values of (ω) were used which restricted a complete comparison between all published optimization results; (2) some published results are mistakenly unsatisfied the hydraulic head constraints; (3) most algorithms reached optimal solution after several runs (trials), but with craftiness only the results of the best run are always mentioned; i.e. computational effort for tuning the algorithm control variables and cost of running the algorithm several times may be excluded; and (4) there is no unified strategy to investigate different optimization methods used to find the optimal WDNs design, also a clear protocol to necessary results that must be mentioned in the papers are not existed. To the authors' knowledge, nearly all literature studied the optimal design of the three benchmark WDNs are surveyed, which make assistance to future researchers.

Based on different optimal results borrowed from the literature, two performance metrics are created which are applicable only for algorithms that reached optimal solutions; i.e. η_{cost} = 1. The first metric measures global performance of algorithm in case of having only the data of one run, $\eta_{algorithm}$. That performance is based on the number of generations with respect to the dimensionality of the solution space, η_{gen}, and the number of function evaluations to the optimal solution, η_{eval}. The second metric, which is more realistic, measures the average global performance, $\eta_{avg\text{-}algorithm}$, for any algorithm with available published results of different runs. That performance considers the same variables of the first one in addition of using both of the degree of reliability of catching optimal solution and the deviation of the average results from the optimal one. Description of different metrics are presented in a graphical form.

Precise investigation of the literature results shows the superior global performance of the FDE algorithm using the two suggested performance metrics. The main advantage of that algorithm is that it can converge to the optimal minimum in far smaller number of function evaluations with respect to the other algorithms. While some algorithms can reach the optimal cost at every run, they are expended much computational effort in comparison with the FDE. Thus, for the same computational effort, the FDE algorithm, with a little lower probability of success, can reach the optimal solution several times. That algorithm shows a higher reliability in case of handling medium WDN than for small WDN.

Table 7
Algorithms performance evaluation for the New York tunnels network.

Authors	Algorithm	N_{gen}	Minimum	Average		Performance metrics			Algorithm efficiency	
			$N_{obj\text{-}eval}$	$N_{avg\text{-}eval}$	$C_{avg\text{-}min}$ ($M)	η_{gen} (%)	η_{eval} (%)	$\eta_{success}$ (%)	$\eta_{algorithm}$ (%)	$\eta_{avg\text{-}algorithm}$ (%)
Maier et al. [25]	ACO	50,000	7,014	13,928	–	81.4	84.8	–	81.527	–
Broad et al. [68]	GA-ANN	–	–	800,000	–	–	–	–	–	–
Zecchin et al. [48]	MMAS	50,000	22,635	30,711	38.84	81.4	82.8	60	81.517	80.643
Afshar [115]	ACO	30,000	18,200	–	–	82.3	83.2	–	82.387	–
Afshar and Mariño [129]	GA[a]	40,000	14,600	16,860	38.77	81.8	83.5	60	81.900	81.028
Afshar and Mariño [129]	GA[b]	40,000	11,200	13,420	39.01	81.8	84.0	70	81.902	81.289
Lin et al. [56]	SS	60,440	–	57,583	–	81.1	–	65	–	–
Afshar [130]	ACO[c]	20,000	10,650	14,450	38.81	83.0	84.1	60	83.081	82.208
Afshar [130]	ACO[d]	20,000	14,450	16,170	38.77	83.0	83.5	60	83.079	82.207
Montalvo et al. [131]	PSO	80,000	2,400	–	38.77	80.6	86.6	–	80.737	–
Afshar [101]	cGA	15,000	7,760	–	–	83.5	84.6	83.3	83.573	–
Geem [73]	PSHS	10,000	4,475	5,923	–	84.2	85.6	–	84.267	–
Tolson et al. [70]	$PSO_{variant}$	80,000	–	–	38.83	80.6	–	30	–	–
Tolson et al. [70]	HD-DDS	50,000	–	46,000	38.64	81.4	–	86	–	81.254
Bolognesi et al. [40]	GHEST	50,000	2,100	7,795	38.64	81.4	86.9	100	81.537	81.526
Dandy et al. [13]	GA	100,000	–	–	38.965	80.2	–	46.7	–	–
Dandy et al. [13]	PSO	100,000	–	–	38.929	80.2	–	33.3	–	–
Dandy et al. [13]	DE	100,000	–	–	40.333	80.2	–	73.3	–	–
Suribabu [32]	DE	10,000	3,220	5,494	–	84.2	86.1	70.7	84.270	–
Vasan and Simonovic [128]	DE	–	30,701	–	–	–	82.3	–	–	–
Zheng et al. [132]	GA	100,000	–	49,450	38.998	80.2	–	45.4	–	78.983
Zheng et al. [96]	DE1[e]	300,000	–	40,726	38.68	78.3	–	86	–	78.208
Zheng et al. [96]	DE2[e]	300,000	–	3,726	39.70	78.3	–	12	–	74.865
Zheng et al. [96]	DE3[e]	300,000	–	24,462	38.76	78.3	–	56	–	77.482
Zheng et al. [96]	DE4[e]	300,000	–	44,152	38.68	78.3	–	86	–	78.207
Zheng et al. [96]	DE5[e]	300,000	–	184,966	38.64	78.3	–	96	–	78.383
Zheng et al. [72]	NLP-DE1[f]	20,000	–	8,277	38.64	83.0	–	99	–	83.066
Zheng et al. [72]	NLP-DE2[g]	20,000	–	10,631	38.64	83.0	–	99	–	83.064
Dong et al. [103]	DE	50,000	–	18,271	38.65	81.4	–	99	–	81.501
Dong et al. [103]	GA	100,000	–	26,944	38.96	80.2	–	64	–	79.573
Sedki and Ouazar [74]	PSO	13,800	–	3,570	38.77	83.6	–	–	–	–
Zheng et al. [14]	SDE	200,000	–	12,855	38.65	79.0	–	97	–	79.113
Zheng et al. [14]	DDE	200,000	–	13,214	38.66	79.0	–	93	–	79.041
Zheng et al. [14]	CGA	200,000	–	44,324	39.04	79.0	–	50	–	77.969
Zheng et al. [14]	SGA	200,000	–	54,789	39.25	79.0	–	45	–	77.785
Zheng et al. [51]	SADE	9,227	–	6,598	38.64	84.3	–	92	–	84.259
Aghdam et al. [63]	SFLA	–	–	7,541	38.70	–	–	85	–	–
Marchi et al. [82]	GA_{trad}	500,000	100,000	–	38.847	77.5	80.2	63.3	77.589	–
Marchi et al. [82]	GA_{mod}	500,000	100,000	–	38.662	77.5	80.2	90	77.589	–
Marchi et al. [82]	PSO	500,000	100,000	–	39.81	77.5	80.2	23.3	77.589	–
Marchi et al. [82]	DE	500,000	100,000	–	38.667	77.5	80.2	90	77.589	–
Moosavian and Roodsari [55]	SLC1[h]	100,000	–	7,821	38.81	80.2	–	80	–	79.965
Moosavian and Roodsari [55]	SLC2[i]	100,000	–	15,764	38.64	80.2	–	100	–	80.341
Sheikholeslami et al. [31]	CSS	2,000	2,000	–	40.08	86.9	86.9	–	87.011	–
Zheng et al. [65]	BLP-DE	7,500	–	3,486	38.64	84.7	–	100	–	84.759
Sadollah et al. [46]	MBA	10,000	3,450	–	38.99	84.2	86.0	–	84.269	–
Sadollah et al. [46]	IMBA	10,000	2,050	–	38.71	84.2	86.9	–	84.274	–
Zheng [33]	SDE	200,000	–	50,700	38.65	79.0	–	–	–	–
Zheng [33]	dDE	200,000	–	50,500	38.64	79.0	–	–	–	–
Zheng [33]	MdDE	200,000	–	26,200	38.64	79.0	–	–	–	–
Zheng [33]	SADE	200,000	–	23,500	38.64	79.0	–	–	–	
Moeini and Moulaei [106]	ACOA2[j]	100,000	9,900	–	45.87	80.2	84.2	–	80.345	–
Moosavian and Lence [36]	FDE	1,000	238	472	52.87	88.1	90.6	47	88.208	86.763
Moosavian and Lence [36]	FDE	5,000	238	1,454	38.92	85.4	90.6	84	85.471	85.155
Moosavian and Lence [36]	FDE	10,000	238	1,685	38.69	84.2	90.6	89	84.292	84.077
Moosavian and Lence [36]	FDE	100,000	238	4,193	38.64	80.2	90.6	100	80.377	80.353

Optimal Cost C_{opt} = 38.640 M$. Maximum Cost C_{max} = 294,103,200 $. Cost Efficiency η_{cost} = 100%. Search space $N_{space} = 16^{21} = 1.934 \times 10^{25}$.
[a] GA with internal self-adaptive penalty method;
[b] GA with external self-adaptive penalty method;
[c] ACO with internal self-adaptive penalty method;
[d] ACO with external self-adaptive penalty method;
[e] Five mutation strategies in DE: DE1-Rand1, DE2-Best1, DE3-Best2, DE4-CurrentToBest2, and DE5-Rand2;
[f] NLP-DE1: DE seeded with two tailored pipe diameters;
[g] NLP-DE2: DE seeded with four tailored pipe diameters;
[h] SLC1 = SLC without relegation and promotion;
[i] SLC2 = SLC with relegation and promotion; and
[j] ACOA2 = ACOA with Max-Min Ant System (MMAS).

In reality, optimal performance is reached after an exhaustive computational effort to tune any algorithm dependent control variables. Therefore, another very important advantage of the FDE algorithm, that is not included in nearly all other algorithms, it's no need of making a sensitivity analysis because the FDE algorithm is independent of control variables. Thus, a recommended future work is studying the effect of that algorithm on intermediate and large WDNs.

Due to the limitation of the computational cost, it is important to remember that all results presented here are unfairly based on stabilizing at least one group of variables as: (1) control and tuning parameters of EAs; (2) different forms of the EA; (3) complexity of the studied problem (e.g., the solution space, the intensity of the local minima); and (4) effect of nodal demands and pipe roughness, and degree of tortuosity along the solution space, as studied by Lee et al. [83]. Therefore, the authors recommend paying attention to these points in future researches.

References

[1] Shahzad G, Rehan R, Fahim M. Rapid performance evaluation of water supply services for strategic planning. Civ Eng J 2019;5(5):1197–204. doi: https://doi.org/10.28991/cej-2019-03091324.

[2] Zhang L. Big data, knowledge mapping for sustainable development: A water quality index case study. Emerg Sci J 2019;3(4):249–54. doi: https://doi.org/10.28991/esj-2019-01187.

[3] Basmenji AB, Mojtahedi A, Rezayi A. Analysis of the urban water requisition demand for the purpose of re-engineering and water network optimization (Case study: Tabriz' Eram urban area). Civ Eng J 2017;3(9):672–81. doi: https://doi.org/10.21859/cej-03094.

[4] Maier HR, Razavi S, Kapelan Z, Matott LS, Kasprzyk J, Tolson BA. Introductory overview: Optimization using evolutionary algorithms and other metaheuristics. Environ Model Softw 2019;114(4):195–213. doi: https://doi.org/10.1016/j.envsoft.2018.11.018.

[5] Ruiz-Vanoye JA, Barrera-Cámara R, Díaz-Parra O, Fuentes-Penna A, Perez Ortega J, Bernabe Loranca B, et al. Surveying the optimization problems of water distribution networks. Pol J Environ Stud 2018;27(4):1425–32. doi: https://doi.org/10.15244/pjoes/76502.

[6] Mala-Jetmarova H, Sultanova N, Savic D. Lost in optimisation of water distribution systems? A literature review of system design. Water 2018;10(3):307. doi: https://doi.org/10.3390/w10030307.

[7] Savić D, Mala-Jetmarova H, Sultanova N. History of optimization in water distribution system analysis. WDSA/CCWI Joint Conference Proceedings (Vol. 1),. Ontario, Canada: Kingston; 2018.

[8] Monsef H, Naghashzadegan M, Jamali A, Farmani R. Comparison of evolutionary multi objective optimization algorithms in optimum design of water distribution network. Ain Shams Eng J 2019;10(1):103–11. doi: https://doi.org/10.1016/j.asej.2018.04.003.

[9] Atkinson S, Farmani R, Memon FA, Butler D. Reliability indicators for water distribution system design: Comparison. J Water Resour Plann Manage 2014;140(2):160–8. doi: https://doi.org/10.1061/(ASCE)WR.1943-5452.0000304.

[10] Hao GS, Chen CS, Wang GG, Huang YQ, Zhou DX, Zhang ZJ. In: Efficiency and effectiveness metrics in evolutionary algorithms and their application. Cham: Springer; 2015. pp. 1–12. doi: https://doi.org/10.1007/978-3-319-22186-1_1.

[11] Gomes WJ, Beck AT, Lopez RH, Miguel LF. A probabilistic metric for comparing metaheuristic optimization algorithms. Struct Saf 2018;70:59–70. doi: https://doi.org/10.1016/j.strusafe.2017.10.006.

[12] Zecchin AC, Maier HR, Simpson AR, Leonard M, Nixon JB. Ant colony optimization applied to water distribution system design: Comparative study of five algorithms. J Water Resour Plann Manage 2007;133(1):87–92. doi: https://doi.org/10.1061/(ASCE)0733-9496(2007)133:1(87).

[13] Dandy G.C., Wilkins A., Rohrlach H. A methodology for comparing evolutionary algorithms for optimizing water distribution systems. In: Proceeding of 12th Water Distribution System Analysis Symposium, Tucson, Arizona, 2010, pp. 786–798. doi: https://doi.org/10.1061/41203(425)73.

[14] Zheng F, Simpson AR, Zecchin A. A performance comparison of differential evolution and genetic algorithm variants applied to water distribution system optimization. World Environmental and Water Resources Congress 2012: Crossing Boundaries 2012:2954–63. doi: https://doi.org/10.1061/9780784412312.296.

[15] Mora-Melia D, Iglesias-Rey PL, Martinez-Solano FJ, Fuertes-Miquel VS. Design of water distribution networks using a pseudo-genetic algorithm and sensitivity of genetic operators. Water Resour Manage 2013;27(12):4149–62. doi: https://doi.org/10.1007/s11269-013-0400-6.

[16] Mora-Melia D, Iglesias-Rey PL, Martinez-Solano FJ, Ballesteros-Pérez P. Efficiency of evolutionary algorithms in water network pipe sizing. Water Resour Manage 2015;29(13):4817–31. doi: https://doi.org/10.1007/s11269-015-1092-x.

[17] Mora-Melià D, Gutiérrez-Bahamondes JH, Iglesias-Rey PL, Martínez-Solano FJ. Efficiency criteria as a solution to the uncertainty in the choice of population size in population-based algorithms applied to water network optimization. Water 2016;8(12):583. doi: https://doi.org/10.3390/w8120583.

[18] Mora-Melià D, Martínez-Solano FJ, Iglesias-Rey PL, Gutiérrez-Bahamondes JH. Population size influence on the efficiency of evolutionary algorithms to design water networks. Procedia Eng 2017;186:341–8. doi: https://doi.org/10.1016/j.proeng.2017.03.209.

[19] El-Ghandour HA, Elbeltagi E. Comparison of five evolutionary algorithms for optimization of water distribution networks. J Comput Civ Eng 2018;32(1):04017066. doi: https://doi.org/10.1061/(ASCE)CP.1943-5487.0000717.

[20] Moosavian N, Lence B. Testing evolutionary algorithms for optimization of water distribution networks. Can J Civ Eng 2018;46(5):391–402. doi: https://doi.org/10.1139/cjce-2018-0137.

[21] Alatas B. Sports inspired computational intelligence algorithms for global optimization. Artif Intell Rev 2019;52(3):1579–627. doi: https://doi.org/10.1007/s10462-017-9587-x.

[22] Vasant P, Kose U, Watada J. Metaheuristic techniques in enhancing the efficiency and performance of thermo-electric cooling devices. Energies 2017;10(11):1703. doi: https://doi.org/10.3390/en10111703.

[23] Chicco G, Mazza A. Heuristic optimization of electrical energy systems: Refined metrics to compare the solutions. Sustain Energy Grids Netw 2019;17:100197. doi: https://doi.org/10.1016/j.segan.2019.100197.

[24] De Corte A, Sörensen K. Optimisation of gravity-fed water distribution network design: A critical review. Eur J Oper Res 2013;228(1):1–10. doi: https://doi.org/10.1016/j.ejor.2012.11.046.

[25] Maier HR, Simpson AR, Zecchin AC, Foong WK, Phang KY, Seah HY, et al. Ant colony optimization for design of water distribution systems. J Water Resour Plann Manage 2003;129(3):200–9. doi: https://doi.org/10.1061/(ASCE)0733-9496(2003)129:3(200).

[26] Reca J, Martínez J, Lopez R. A hybrid water distribution networks design optimization method based on a search space reduction approach and a genetic algorithm. Water 2017;9(11):845. doi: https://doi.org/10.3390/w9110845.

[27] Perelman L, Ostfeld A. An adaptive heuristic cross-entropy algorithm for optimal design of water distribution systems. Eng Optim 2007;39(4):413–28. doi: https://doi.org/10.1080/03052150601154671.

[28] Jabbary A, Podeh HT, Younesi H, Haghiabi AH. Development of central force optimization for pipe-sizing of water distribution networks. Water Sci Tech Water Supply 2016;16(5):1398–409. doi: https://doi.org/10.2166/ws.2016.051.

[29] Afshar MH, Mariño MA. A convergent genetic algorithm for pipe network optimization. Scientia Iranica 2005;12(4):392–401.

[30] Sheikholeslami R, Zecchin AC, Zheng F, Talatahari S. A hybrid cuckoo–harmony search algorithm for optimal design of water distribution systems. J Hydroinf 2016;18(3):544–63. doi: https://doi.org/10.2166/hydro.2015.174.

[31] Sheikholeslami R, Kaveh A, Tahershamsi A, Talatahari S. Application of charged system search algorithm to water distribution networks optimization. Int J Optim Civil Eng 2014;4(1):41–58.

[32] Suribabu CR. Differential evolution algorithm for optimal design of water distribution networks. J Hydroinf 2010;12(1):66–82. doi: https://doi.org/10.2166/hydro.2010.014.

[33] Zheng F. Comparing the real-time searching behavior of four differential-evolution variants applied to water-distribution-network design optimization. J Water Resour Plann Manage 2015;141(10):04015016. doi: https://doi.org/10.1061/(ASCE)WR.1943-5452.0000534.

[34] Sheikholeslami R, Talatahari S. Developed swarm optimizer: A new method for sizing optimization of water distribution systems. J Comput Civ Eng 2016;30(5):04016005. doi: https://doi.org/10.1061/(ASCE)CP.1943-5487.0000552.

[35] Poojitha SN, Singh G, Jothiprakash V. Improving the optimal solution of GoYang network – using genetic algorithm and differential evolution. Water Supply 2020;20(1):95–102. doi: https://doi.org/10.2166/ws.2019.139.

[36] Moosavian N, Lence BJ. Fittest individual referenced differential evolution algorithms for optimization of water distribution networks. J Comput Civ Eng 2019;33(6):04019036. doi: https://doi.org/10.1061/(ASCE)CP.1943-5487.0000849.

[37] Simpson AR, Dandy GC, Murphy LJ. Genetic algorithms compared to other techniques for pipe optimization. J Water Resour Plann Manage 1994;120(4):423–43. doi: https://doi.org/10.1061/(ASCE)0733-9496(1994)120:4(423).

[38] Neelakantan T, Suribabu CR. Optimal design of water distribution networks by a modified genetic algorithm. J Civil Environ Eng 2005;1(1):20–34.

[39] Reca J, Martínez J. Genetic algorithms for the design of looped irrigation water distribution networks. Water Resour Res 2006;42:W05416. doi: https://doi.org/10.1029/2005WR004383.

[40] Bolognesi A, Bragalli C, Marchi A, Artina S. Genetic heritage evolution by stochastic transmission in the optimal design of water distribution networks. Adv Eng Softw 2010;41(5):792–801. doi: https://doi.org/10.1016/j.advengsoft.2009.12.020.

[41] Fallah H, Ghazanfari S, Suribabu CR, Rashedi E. Optimal pipe dimensioning in water distribution networks using Gravitational Search Algorithm. ISH J Hydraul Eng 2019:1–14. doi: https://doi.org/10.1080/09715010.2019.1624630.

[42] Mohan S, Babu KS. Optimal water distribution network design with honey-bee mating optimization. J Comput Civ Eng 2010;24(1):117–26. doi: https://doi.org/10.1061/(ASCE)CP.1943-5487.0000018.

[43] Geem ZW, Kim JH, Loganathan GV. Harmony search optimization: application to pipe network design. Int J Model Simulat 2002;22(2):125–33. doi: https://doi.org/10.1080/02286203.2002.11442233.

[44] Ezzeldin R, Djebedjian B, Saafan T. Integer discrete particle swarm optimization of water distribution networks. J Pipeline Syst Eng Pract 2014;5(1):04013013. doi: https://doi.org/10.1061/(ASCE)PS.1949-1204.0000154.

[45] De Corte A, Sörensen K. An iterated local search algorithm for water distribution network design optimization. Networks 2016;67(3):187–98. doi: https://doi.org/10.1002/net.21673.

[46] Sadollah A, Yoo DG, Kim JH. Improved mine blast algorithm for optimal cost design of water distribution systems. Eng Optim 2015;47(12):1602–18. doi: https://doi.org/10.1080/0305215X.2014.979815.

[47] Baños R, Gil C, Reca J, Montoya FG. A memetic algorithm applied to the design of water distribution networks. Appl Soft Comput 2010;10(1):261–6. doi: https://doi.org/10.1016/j.asoc.2009.07.010.

[48] Zecchin AC, Simpson AR, Maier HR, Leonard M, Roberts AJ, Berrisford MJ. Application of two ant colony optimisation algorithms to water distribution system optimisation. Math Comput Model 2006;44(5):451–68. doi: https://doi.org/10.1016/j.mcm.2006.01.005.

[49] Suribabu CR, Neelakantan TR. Particle swarm optimization compared to other heuristic search techniques for pipe sizing. J Environ Informatics 2006;8(1):1–9. doi: https://doi.org/10.3808/jei.200600072.

[50] Loganathan GV, Greene JJ, Ahn TJ. Design heuristic for globally minimum cost water-distribution systems. J Water Resour Plann Manage 1995;121(2):182–92. doi: https://doi.org/10.1061/(ASCE)0733-9496(1995)121:2(182).

[51] Zheng F, Zecchin AC, Simpson AR. Self-adaptive differential evolution algorithm applied to water distribution system optimization. J Comput Civ Eng 2013;27(2):148–58. doi: https://doi.org/10.1061/(ASCE)CP.1943-5487.0000208.

[52] Shende S, Chau KW. Design of water distribution systems using an intelligent simple benchmarking algorithm with respect to cost optimization and computational efficiency. Water Supply 2019;19(7):1892–8. doi: https://doi.org/10.2166/ws.2019.065.

[53] Liong SY, Atiquzzaman M. Optimal design of water distribution network using shuffled complex evolution. J Inst Eng, Singapore 2004;44(1):93–107.

[54] Eusuff MM, Lansey KE. Optimization of water distribution network design using the shuffled frog leaping algorithm. J Water Resour Plann Manage 2003;129(3):210–25. doi: https://doi.org/10.1061/(ASCE)0733-9496(2003)129:3(210).

[55] Moosavian N, Roodsari BK. Soccer league competition algorithm: A novel meta-heuristic algorithm for optimal design of water distribution networks. Swarm Evol Comp 2014;17:14–24. doi: https://doi.org/10.1016/j.swevo.2014.02.002.

[56] Lin MD, Liu YH, Liu GF, Chu CW. Scatter search heuristic for least-cost design of water distribution networks. Eng Optim 2007;39(7):857–76. doi: https://doi.org/10.1080/03052150701503611.

[57] Zhou X, Gao DY, Simpson AR. Optimal design of water distribution networks by a discrete state transition algorithm. Eng. Optim. 2016;48(4):603–28. doi: https://doi.org/10.1080/0305215X.2015.1025775.

[58] Lippai I, Heaney JP, Laguna M. Robust water system design with commercial intelligent search optimizers. J Comput Civ Eng 1999;13(3):135–43. doi: https://doi.org/10.1061/(ASCE)0887-3801(1999)13:3(135).

[59] Fanni A, Liberatore S, Sechi GM, Soro M, Zuddas P. Optimization of water distribution systems by Tabu Search metaheuristic. In: Laguna M, González-Velarde JL, editors. Computing Tools for Modelling, Optimization and Simulation. Kluwer Academic; 2000. pp. 279–98. doi: https://doi.org/10.1007/978-1-4615-4567-5_16.

[60] Sadollah A, Yoo DG, Yazdi J, Kim JH, Choi Y. Application of water cycle algorithm for optimal cost design of water distribution systems. New York: CUNY Academic Works; 2014.

[61] Ezzeldin RM, Djebedjian B. Optimal design of water distribution networks using whale optimization algorithm. Urban Water J 2020;17(1):14–22. doi: https://doi.org/10.1080/1573062X.2020.1734635.

[62] Djebedjian B., Abdel-Gawad H.A.A., Ezzeldin R., Yaseen A., Rayan M.A. Evaluation of capacity reliability-based and uncertainty-based optimization of water distribution systems. In: Proc., 11th International Water Technology Conference, (IWTC11), Sharm El-Sheikh, Egypt, March 15-18, 2007, pp. 565–587.

[63] Aghdam KM, Mirzaee I, Pourmahmood N, Aghababa MP. Adaptive mutated momentum shuffled frog leaping algorithm for design of water distribution networks. Arab J Sci Eng 2014;39(11):7717–27. doi: https://doi.org/10.1007/s13369-014-1367-1.

[64] Aghdam KM, Mirzaee I, Pourmahmood N, Aghababa MP. Design of water distribution networks using accelerated momentum particle swarm optimisation technique. J Exp Theoret Artif Intell 2014;26(4):459–75. doi: https://doi.org/10.1080/0952813X.2013.863227.

[65] Zheng F, Simpson AR, Zecchin AC. Coupled binary linear programming–differential evolution algorithm approach for water distribution system optimization. J Water Resour Plann Manage 2014;140(5):585–97. doi: https://doi.org/10.1061/(ASCE)WR.1943-5452.0000367.

[66] Delir S, Foroughi-Asl A, Talatahari S. A hybrid charged system search - firefly algorithm for optimization of water distribution networks. Int J Optim Civil Eng 2019;9(2):273–90.

[67] Aghdam KM, Mirzaee I, Pourmahmood N, Aghababa MP. Design of water distribution networks via a novel fractional succedaneum shuffled leaping method. J Mech 2015;31(4):369–80. doi: https://doi.org/10.1017/jmech.2014.94.

[68] Broad DR, Dandy GC, Maier HR. Water distribution system optimization using metamodels. J Water Resour Plann Manage 2005;131(3):172–80. doi: https://doi.org/10.1061/(ASCE)0733-9496(2005)131:3(172).

[69] Haghighi A, Samani HM, Samani ZM. GA-ILP method for optimization of water distribution networks. Water Resour Manage 2011;25(7):1791–808. doi: https://doi.org/10.1007/s11269-011-9775-4.

[70] Tolson BA, Asadzadeh M, Maier HR, Zecchin A. Hybrid discrete dynamically dimensioned search (HD-DDS) algorithm for water distribution system design optimization. Water Resour Res 2009;45(12):W12416. doi: https://doi.org/10.1029/2008WR007673.

[71] Qi X, Li K, Potter WD. Estimation of distribution algorithm enhanced particle swarm optimization for water distribution network optimization. Front Environ Sci Eng 2016;10(2):341–51. doi: https://doi.org/10.1007/s11783-015-0776-z.

[72] Zheng F, Simpson AR, Zecchin AC. A combined NLP-differential evolution algorithm approach for the optimization of looped water distribution systems. Water Resour Res 2011;47(W08531):1–18. doi: https://doi.org/10.1029/2011WR010394.

[73] Geem ZW. Particle-swarm harmony search for water network design. Eng Optim 2009;41(4):297–311. doi: https://doi.org/10.1080/03052150802449227.

[74] Sedki A, Ouazar D. Hybrid particle swarm optimization and differential evolution for optimal design of water distribution systems. Adv Eng Inform 2012;26(3):582–91. doi: https://doi.org/10.1016/j.aei.2012.03.007.

[75] Reca J, Martínez J, Gil C, Baños R. Application of several meta-heuristic techniques to the optimization of real looped water distribution networks. Water Resour Manage 2008;22(10):1367–79. doi: https://doi.org/10.1007/s11269-007-9230-8.

[76] Dolan ED, Moré JJ. Benchmarking optimization software with performance profiles. Math Program 2002;91(2):201–13. doi: https://doi.org/10.1007/s101070100263.

[77] Moré JJ, Wild S. Benchmarking derivative-free optimization algorithms. SIAM J Optim 2009;20(1):172–91. doi: https://doi.org/10.1137/080724083.

[78] Solomatine D.P. Genetic and other global optimization algorithms - Comparison and use in calibration problems. In: Proc., 3rd International Conference on Hydroinformatics, Copenhagen, Denmark, 1998, pp. 1021–1028.

[79] Beiranvand V, Hare W, Lucet Y. Best practices for comparing optimization algorithms. Optim Eng 2017;18(4):815–48. doi: https://doi.org/10.1007/s11081-017-9366-1.

[80] Kavetski D, Qin Y, Kuczera G. The fast and the robust: Trade-offs between optimization robustness and cost in the calibration of environmental models. Water Resour Res 2018;54(11):9432–55. doi: https://doi.org/10.1029/2017WR022051.

[81] Mora-Melia D, Iglesias-Rey PL, Martínez-Solano FJ, Muñoz-Velasco P. The efficiency of setting parameters in a modified shuffled frog leaping algorithm applied to optimizing water distribution networks. Water 2016;8(5):182. doi: https://doi.org/10.3390/w8050182.

[82] Marchi A, Dandy G, Wilkins A, Rohrlach H. Methodology for comparing evolutionary algorithms for optimization of water distribution systems. J Water Resour Plann Manage 2014;140(1):22–31. doi: https://doi.org/10.1061/(ASCE)WR.1943-5452.0000321.

[83] Lee HM, Jung D, Sadollah A, Lee EH, Kim JH. Performance comparison of metaheuristic optimization algorithms using water distribution system design benchmarks. In: Harmony Search and Nature Inspired Optimization Algorithms. Singapore: Springer; 2019. pp. 97–104. doi: https://doi.org/10.1007/978-981-13-0761-4_10.

[84] Simpson A.R., Maier H.R., Foong W.K., Phang K.Y., Seah H.Y., Tan C.L. Selection of parameters for ant colony optimization applied to the optimal design of water distribution systems. In: Proc., International Congress on Modeling and Simulation, Canberra, Australia, 2001, pp. 1931–1936.

[85] Abdel-Gawad HA. Optimal design of pipe networks by an improved genetic algorithm. In: Proc., Sixth International Water Technology Conference, (IWTC 2001), Alexandria. Egypt 2001:155–66.

[86] Zecchin AC, Simpson AR, Maier HR, Nixon JB. Parametric study for an ant algorithm applied to water distribution system optimization. IEEE Trans Evol Comput 2005;9(2):175–91. doi: https://doi.org/10.1109/TEVC.2005.844168.

[87] Ayad AR, Awad HA, Yassin AA. Parametric analysis for genetic algorithms handling parameters. Alexandria Eng J 2013;52(1):99–111. doi: https://doi.org/10.1016/j.aej.2012.10.007.

[88] Giudicianni C, Di Nardo A, Di Natale M, Greco R, Santonastaso G, Scala A. Topological taxonomy of water distribution networks. Water 2018;10(4):444. doi: https://doi.org/10.3390/w10040444.

[89] Wang Q, Guidolin M, Savic D, Kapelan Z. Two-objective design of benchmark problems of a water distribution system via MOEAs: Towards the best-known approximation of the true Pareto front. J Water Resour Plann Manage 2015;141(3):04014060. doi: https://doi.org/10.1061/(ASCE)WR.1943-5452.0000460.

[90] Alperovits E, Shamir U. Design of optimal water distribution systems. Water Resour Res 1977;13(6):885–900. doi: https://doi.org/10.1029/WR013i006p00885.

[91] Fujiwara O, Khang DB. A two-phase decomposition method for optimal design of looped water distribution networks. Water Resour Res 1990;26(4):539–49. doi: https://doi.org/10.1029/WR026i004p00539.

[92] Schaake JC, Lai D. Linear programming and dynamic programming applications to water distribution network design. Report 116, Hydrodynamics Laboratory. Department of Civil Engineering 1969.

[93] Quindry GE, Liebman JC, Brill ED. Optimization of looped water distribution systems. J Environ Eng Div 1981;107(4):665–79.

[94] Savic DA, Walters GA. Genetic algorithms for least-cost design of water distribution networks. J Water Resour Plann Manage 1997;123(2):67–77. doi: https://doi.org/10.1061/(ASCE)0733-9496(1997)123:2(67).

[95] Rossman LA. EPANET 2 users manual, Rep. EPA/600/R-00/057. Water Supply and Water Resources Division. National Risk Management Research Laboratory. Cincinnati: United States Environmental Protection Agency; 2000.

[96] Zheng F, Simpson AR, Zecchin A. Performance study of differential evolution with various mutation strategies applied to water distribution system optimization. In: World Environmental and Water Resources Congress

2011. Bearing Knowledge for Sustainability; 2010. pp. 166–76. doi: https://doi.org/10.1061/41173(414)18.
[97] Abebe AJ, Solomatine DP. Application of global optimization to the design of pipe networks. CopenhagenNetherlands: Balkema; 1999. p. 989–96.
[98] Prasad TD, Park NS. Multiobjective genetic algorithms for design of water distribution networks. J Water Resour Plann Manage 2004;130(1):73–82. doi: https://doi.org/10.1061/(ASCE)0733-9496(2004)130:1(73).
[99] Djebedjian B., Yaseen A., Rayan M.A. A new adaptive penalty method for constrained genetic algorithm and its application to water distribution systems. In: Proc., Ninth International Water Technology Conference, (IWTC 2005), Sharm El-Sheikh, Egypt, 2005, pp. 1077–1099.
[100] Suribabu CR, Neelakantan TR. Design of water distribution networks using particle swarm optimization. J Urban Water 2006;3(2):111–20. doi: https://doi.org/10.1080/15730620600855928.
[101] Afshar MH. Application of a compact genetic algorithm to pipe network optimization problems. Scientia Iranica, Trans A: Civ Eng 2009;16(3):264–71.
[102] Chandramouli S, Malleswararao P. Reliability based optimal design of a water distribution network for municipal water supply. Int J Eng Technol 2011;3(1):13–9.
[103] Dong XL, Liu SQ, Tao T, Li SP, Xin KL. A comparative study of differential evolution and genetic algorithms for optimizing the design of water distribution systems. J Zhejiang University - SCIENCE A (Applied Physics & Engineering) 2012;13(9):674–86. doi: https://doi.org/10.1631/jzus.A1200072.
[104] Babu KSJ, Vijayalakshmi DP. Self-adaptive PSO-GA hybrid model for combinatorial water distribution network design. J Pipeline Syst Eng Pract 2013;4(1):57–67. doi: https://doi.org/10.1061/(ASCE)PS.1949-1204.0000113.
[105] Uma R. Optimal design of water distribution network using differential evolution. Int J Sci Res (IJSR) 2016;5(11):1515–20.
[106] Moeini R, Moulaei SAM. Simulation-optimization model for design of water distribution system using ant based algorithms. The Journal of Engineering Research (TJER) 2018;15(1):42–60. doi: https://doi.org/10.24200/tjer.vol15iss1pp42-60.
[107] Surco DF, Vecchi TP, Ravagnani MA. Optimization of water distribution networks using a modified particle swarm optimization algorithm. Water Sci Tech Water Supply 2018;18(2):660–78. doi: https://doi.org/10.2166/ws.2017.148.
[108] Abdy Sayyed MAH, Gupta R, Tanyimboh T. Combined flow and pressure deficit-based penalty in GA for optimal design of water distribution network. ISH J Hydraul Eng 2019:1–11. doi: https://doi.org/10.1080/09715010.2019.1604180.
[109] Praneeth P, Vasan A, Raju KS. Pipe size design optimization of water distribution networks using water cycle algorithm. In: Harmony Search and Nature Inspired Optimization Algorithms. Singapore: Springer; 2019. pp. 1057–67. doi: https://doi.org/10.1007/978-981-13-0761-4_99.
[110] Goulter IC, Lussier BM, Morgan DR. Implications of head loss path choice in the optimization of water distribution networks. Water Resour Res 1986;22(5):819–22. doi: https://doi.org/10.1029/WR022i005p00819.
[111] Kessler A, Shamir U. Analysis of the linear programming gradient method for optimal design of water supply networks. Water Resour Res 1989;25(7):1469–80. doi: https://doi.org/10.1029/WR025i007p01469.
[112] Cunha MDC, Sousa J. Water distribution network design optimization: Simulated annealing approach. J Water Resour Plann Manage 1999;125(4):215–21. doi: https://doi.org/10.1061/(ASCE)0733-9496(1999)125:4(215).
[113] Wu ZY, Boulos PF, Orr CH, Ro JJ. Using genetic algorithms to rehabilitate distribution systems. J Am Water Works Assn 2001;93(11):74–85. doi: https://doi.org/10.1002/j.1551-8833.2001.tb09335.x.
[114] Geem ZW. Optimal cost design of water distribution networks using harmony search. Eng Optim 2006;38(3):259–80. doi: https://doi.org/10.1080/03052150500467430.
[115] Afshar MH. Application of ant algorithm to pipe network optimization. Iran J Sci Technol 2007;31(B5):487–500.
[116] Kadu MS, Gupta R, Bhave PR. Optimal design of water networks using a modified genetic algorithm with reduction in search space. J Water Resour Plann Manage 2008;134(2):147–60. doi: https://doi.org/10.1061/(ASCE)0733-9496(2008)134:2(147).
[117] Sung Y, Lin M, Lin Y, Liu Y. Tabu search solution of water distribution network optimization. J Environ Eng Manage 2007;17(3):177–87.
[118] Singh KP, Kansal ML, Deep K. GA-NR for optimal design of water distribution networks. Int J Oper Res 2014;20(3):241–61. doi: https://doi.org/10.1504/IJOR.2014.062455.
[119] Sonak VV, Bhave PR. Global optimum tree solution for single-source looped water distribution networks subjected to a single loading pattern. Water Resour Res 1993;29(7):2437–43. doi: https://doi.org/10.1029/93WR00289.
[120] Eiger G, Shamir U, Ben-Tal A. Optimal design of water distribution networks. Water Resour Res 1994;30(9):2637–46. doi: https://doi.org/10.1029/94WR00623.
[121] Varma KVK, Narasimhan S, Bhallamudi SM. Optimal design of water distribution systems using NLP method. J Environ Eng 1997;123(4):381–8. doi: https://doi.org/10.1061/(ASCE)0733-9372(1997)123:4(381).
[122] Sherali HD, Subramanian S, Loganathan GV. Effective relaxations and partitioning schemes for solving water distribution network design problems to global optimality. J Global Optim 2001;19(1):1–26. doi: https://doi.org/10.1023/A:1008368330827.
[123] Ghajarnia N, Bozorg Haddad O, Mariño MA. Performance of a novel hybrid algorithm in the design of water networks. Proc Inst Civ Eng: Water Manage 2011;164(4):173–91. doi: https://doi.org/10.1680/wama.1000028.
[124] Geem Z.W. Improved harmony search from ensemble of music players. Knowledge-Based Intelligent Information and Engineering Systems, (B. Gabrys, R.J. Howlett, L.C. Jain, eds), Lecture Notes in Artificial Intelligence, 4251, 2006, pp. 86–93. doi: https://doi.org/10.1007/11892960_11.
[125] Bi W, Xu Y, Wang H. Comparison of searching behaviour of three evolutionary algorithms applied to water distribution system design optimization. Water 2020;12(3):695. doi: https://doi.org/10.3390/w12030695.
[126] Cunha MC, Ribeiro L. Tabu search algorithms for water network optimization. Eur J Oper Res 2004;157(3):746–58. doi: https://doi.org/10.1016/S0377-2217(03)00242-X.
[127] Chu CW, Lin MD, Liu GF, Sung YH. Application of immune algorithms on solving minimum-cost problem of water distribution network. Math. Comput. Model. 2008;48(11–12):1888–900. doi: https://doi.org/10.1016/j.mcm.2008.02.008.
[128] Vasan A, Simonovic SP. Optimization of water distribution network design using differential evolution. J Water Resour Plann Manage 2010;136(2):279–87. doi: https://doi.org/10.1061/(ASCE)0733-9496(2010)136:2(279).
[129] Afshar MH, Mariño MA. A parameter-free self-adapting boundary genetic search for pipe network optimization. Comput Optim Appl 2007;37(1):83–102. doi: https://doi.org/10.1007/s10589-007-9016-1.
[130] Afshar MH. Penalty adapting ant algorithm: Application to pipe network optimization. Eng Optim 2008;40(10):969–87. doi: https://doi.org/10.1080/03052150802236079.
[131] Montalvo I, Izquierdo J, Pérez R, Tung MM. Particle swarm optimization applied to the design of water supply systems. Comput Math Appl 2008;56(3):769–76. doi: https://doi.org/10.1016/j.camwa.2008.02.006.
[132] Zheng F, Simpson AR, Zecchin AC. A method for assessing the performance of genetic algorithm optimization for water distribution design, 2010. p. 771–85. doi: https://doi.org/10.1061/41203(425)72.

Berge Djebedjian is a Professor at Mechanical Power Engineering Department, Mansoura University, Egypt. He received the B.Sc. and M.Sc. (Mechanical Power Engineering, Mansoura University) in 1981 and 1986. He received the Ph.D. degree in 1997 (Conservatoire National des Arts et Métiers, CNAM, Paris, France). He has authored over 60 papers in various journals and conference proceedings. His research interests are in the areas of water distribution networks, computational fluid dynamics, and desalination.

Associate Professor Hossam A.A. Abdel-Gawad at Mansoura University, Faculty of Engineering, Irrigation and Hydraulics Engineering Department. He has earned his B.Sc. and M.Sc. (Civil Engineering, Alexandria University) 1983, and 1990, Postgraduate Diploma in Hydraulic Engineering (IHE**,** Delft, Netherlands) (1992), Ph.D. (Civil Engineering from Hydraulic Department, Faculty of Civil Engineering, Slovak University of Technology, Bratislava, Slovakia) (1999). His research areas of interests are groundwater simulation, pollution, management, and pipe networks.

Riham M. Ezzeldin is Assistant Professor at Irrigation and Hydraulics Engineering Department, Faculty of Engineering, Mansoura University. She received Ph.D. and M.Sc. from Mansoura University. She supervised two M.Sc. theses and published many papers in national and international journals. Her area of interest is Hydraulics.