Sustainable Cities and Society 87 (2022) 104215

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

# A Chaotic Sobol Sequence-based multi-objective evolutionary algorithm for optimal design and expansion of water networks

Swati Sirsant [a], Mohamed A. Hamouda [b,*], Mostafa F. Shaaban [a], Mayyada Salem Al Bardan [c]

[a] Department of Electrical Engineering, Faculty of Engineering, American University of Sharjah, Sharjah, United Arab Emirates
[b] Department of Civil and Environmental Engineering, Faculty of Engineering, United Arab Emirates University, Al Ain, Abu Dhabi, United Arab Emirates
[c] Research and Studies Department, Sharjah Electricity and Water Authority, Sharjah, United Arab Emirates

ARTICLE INFO

*Keywords:*
Multi-objective optimization
Water distribution networks
Reliability assessment
GHG emissions
Expansion
Optimal pump scheduling

ABSTRACT

The design of a water distribution network (WDN) is an optimization problem that is computationally challenging with conflicting objectives. This study offers an enhanced Chaotic Sobol Sequence-based Multi-Objective Self-Adaptive Differential Evolution (CS-MOSADE) algorithm for multi-objective WDN design. The CS-MOSADE algorithm was tested on two benchmark WDNs, and a real WDN. Optimization results indicate that the CS-MOSADE algorithm converged two to three times faster than the MOSADE and NSGA-IIalgorithms and led to better output in terms of even distribution of solutions and convergence towards the true Pareto-optimal front. Smaller spacing metric indicated better uniformity in the obtained solutions; and larger hyper-area and coverage function values depicted better convergence towards the true Pareto-optimal front for the CS-MOSADE algorithm compared to the other algorithms. The CS-MOSADE algorithm was then applied to solve a WDN expansion problem for optimal pump scheduling and minimization of Life Cycle Cost, maximization of reliability and minimization of Green House Gas (GHG) emissions. A significant reduction in GHG emissions of 2.17 x $10^6$ kg was achieved at an additional cost of \$0.55 x $10^7$ when optimal pump scheduling was incorporated in the model of the real WDN over service life of 50 years.

## 1. Introduction

Design of Water distribution networks (WDNs) comprises a very complex optimization problem. The WDN design is a non-deterministic polynomial-time (NP) hard optimization problem, involving several complexities, like non-deterministic nature and a huge search space even for a small-sized problem (Alperovits & Shamir, 1977; Geem, 2006; Marques et al., 2018; Savic & Walters, 1997; Suribabu, 2009). For example, a network with 8 pipes and 14 available pipe sizes would comprise of a search space of $14^8$. The search space increases

*Abbreviations:* ACO, Ant colony optimization; CERI, combined entropy network resilience; CF, coverage function; CNHV, comparative normalised hyper-volume; CS-MOSADE, Chaotic Sobol Sequence based multi-objective self-adaptive differential evolution; Clustered-NA-ACO, clustered non-dominated archiving ant colony optimization; DE, differential evolution; DESAP, differential evolution with self-adaptive population; EA, evolutionary algorithm; EADC, evolutionary algorithm with directed weights for constraint handling; EF, emission factor; EPS, extended period simulation; ESS, energy sustainability score; FADE, fuzzy-adaptive differential evolution; FORM, first-order reliability method; GA, genetic algorithm; GAFO, genetic algorithm based flexibility optimization; GHG, green house gas; HA, hyper-area; HV, hyper-volume; IGD, inverted generational distance; jDE, differential evolution with self-adapting control parameters; LCC, life cycle cost; LP, linear programming; MODE-SaE, multi-objective differential evolution with self-adaptive epsilon; MOSADE-DP, multi-objective self-adaptive differential evolution-dynamic programming; MC, Monte Carlo; MCS, Monte Carlo simulation; WDN, water distribution network; MO-ASMOCH, multi-objective adaptive surrogate modelling-based optimization for constrained hybrid problems; MODE-CSFLA, multi-objective differential evolution-chaos shuffled frog leaping algorithm; MOGA, multi-objective genetic algorithm; MOPSO, multi-objective particle swarm optimization; NYT, NewYork tunnel; NFE, number of function evaluations; NHV, normalised hyper-volume; NLP, non-linear programming; NP, non-deterministic polynomial-time; NSGA-II, non-dominated sorting genetic algorithm-II; PA-DSS, hybrid Pareto archived dynamically dimensioned search; PSO, particle swarm optimization; PVC-O, molecular oriented polyvinyl chloride; QRS, quasi-random sequence; RHV, reduced hyper-volume; RNSGA-II, robust non-dominated sorting genetic algorithm-II; RSM, reliability surrogate measure; SADE, self-adaptive differential evolution algorithm; SAES-RBF, surrogate assisted evolution strategy radial basis function; SAMOHS, self-adaptive multi-objective harmony search; WOA, whale optimization algorithm.

* Corresponding author.
*E-mail address:* m.hamouda@uaeu.ac.ae (M.A. Hamouda).

https://doi.org/10.1016/j.scs.2022.104215
Received 19 March 2022; Received in revised form 28 August 2022; Accepted 25 September 2022
Available online 29 September 2022
2210-6707/

exponentially until it becomes insurmountable for large-scale real-world WDN problems. The computational requirement increases further by consideration of reliability in the problem. Babayan et al. (2005) required nearly 8 h for optimizing NewYork Tunnel (NYT) WDN problem, comprising of 21 links and 19 junctions on employing Robust Non-Dominated Sorting Genetic Algorithm-II (RNSGA-II) adopting 200 as the population size for 500 iterations and 1000 MC samples solved on a system with a 2.6 GHz AMD FX-55 processor. A huge computational time of around 2-3 days was reported by Basupi & Kapelan (2015) for solving the NYT WDN problem employing Genetic Algorithm (GA) taking 100 as the population size for 6500 iterations and 200 MC samples solved on a system with 4-cores and a 2.67 GHz processor. Two loop WDN comprising of 8 links and 6 junctions required 19.72 and 1.211 h of computational time on consideration of hydraulic and mechanical reliabilities respectively on adopting a population size of 200 and maximum iterations of 1000 for solving using Self-Adaptive Differential Evolution Algorithm (SADE) (Sirsant & Reddy, 2020). Several other studies also reported huge computational demands for solving the reliability based WDN design problem (Manolis et al., 2021; Raad et al., 2010; Tanyimboh, 2017). The solution becomes particularly more challenging when Evolutionary Algorithms (EAs) are employed for solving the WDN design problem. For example, if 8 s of computational time is required for estimation of hydraulic reliability of a WDN problem, and is solved using a population size of 300 for maximum iterations of 1000, would require 2,400,000 s (around 28 days).

Various techniques have been applied in past studies to solve the WDN design problem such as linear programming (LP) (Alperovits & Shamir, 1977; Fujiwara et al., 1987; Samani & Mottaghi, 2006), non-linear programming (NLP) (Bragalli et al., 2012; Mansouri et al., 2015), heuristic techniques based on the satisfaction of demand and head constraints (Suribabu, 2012; Todini, 2000) and meta-heuristic techniques such as Genetic Algorithm (GA) (Keedwell & Khu, 2005; Savic & Walters, 1997; van Laarhoven et al., 2018), Particle Swarm Optimization (Ezzeldin et al., 2014; Suribabu & Neelakantan, 2006), Ant Colony Optimization (Maier et al., 2003; Zecchin et al., 2007), Differential Evolution (DE) (Suribabu, 2009; Vasan & Simonovic, 2010), Self-Adaptive Differential Evolution (SADE) (Sirsant & Janga Reddy, 2018; Zheng et al., 2013), Whale optimization algorithm (Ezzeldin & Djebedjian, 2020) etc. Many past studies have shown that meta-heuristic techniques like EAs possess several advantages such as vast exploration of search space and quick convergence (El Ansary & Shalaby, 2014; Muhuri & Nath, 2019; Wu et al., 2021). Many self-adaptive versions of DE were developed such as SADE (Qin & Suganthan, 2005), Fuzzy-Adaptive DE (FADE) (Liu & Lampinen, 2005), DE with Self-Adaptive Population (DESAP) (Teo, 2006), DE with self-adapting control parameters (jDE) (Brest et al., 2006), jDE-2 (Brest et al., 2007). The advantage of SADE over normal DE is that the mutation and crossover parameters are self-adapted by the algorithm itself, saving a lot of computational time in determining the most suitable values of these parameters (which are problem dependent) using sensitivity analysis. Few studies have shown that SADE has faster convergence and higher success rate compared to DE (Nandi & Janga Reddy, 2020; Sirsant & Janga Reddy, 2018; Zheng et al., 2013). More investigations applying EA techniques are needed to support these observations, which requires improvements in the existing EAs or development of new EAs.

Past studies have shown that the WDN design problem should be formulated as a multi-objective optimization problem rather than a single objective problem considering the aspects of cost and reliability (Cunha & Marques, 2020; Prasad & Park, 2004; Vamvakeridou-Lyroudia et al., 2005). Reliability is a measure of the extent of demand fulfillment considering the operational and failure conditions, which can be hydraulic and mechanical (Bao & Mays, 1990). Various past studies have been conducted for estimation of the reliability of WDNs. Shamir & Howard (1981) defined WDN reliability as an estimate of the shortages occurring as a result of failure of network elements. Other popular techniques include minimum cut set method (Su et al. 1987), Monte Carlo Simulation (MCS) method (Bao & Mays, 1990, Xu & Goulter, 1998, Sirsant & Reddy, 2018), first-order reliability method (FORM) method Tolson et al. (2004). Few studies employed fuzzy sets to represent the uncertain water demands (Branisavljević et al., 2009, Shibu & Reddy, 2014, Geranmehr et al., 2019). Other recent studies include recovery-based resilience enhancement strategies (Liu et al., 2020), reliability assessment model based on state space models (Valis et al., 2022). The major drawback of these techniques is that they are very time consuming in nature, and require multiple hydraulic simulations for a single reliability estimation.

To handle the problem of huge computational time, past few studies have proposed several reliability surrogate measures (RSMs) such as entropy (Awumah et al., 1990), resiliency (Todini, 2000), network resilience (Prasad & Park, 2004). These RSMs possess the benefit that their estimation is very easy and involves only a single hydraulic simulation for estimation of one value of RSM. Hence, the computational requirement reduces by a huge extent. Raad et al. (2010), Jung & Kim (2018), Monsef et al. (2019) investigated the performance of various RSMs as an alternative for mechanical and hydraulic failures. These studies found the lack of a single RSM performing efficiently as an alternative for both hydraulic and mechanical reliabilities. Creaco et al. (2016) proposed that optimizing resiliency and loop diameter uniformity index along with cost can lead to more robust solutions compared to consideration of only cost and resiliency. However, this approach requires consideration of three objective optimization formulation, wherein two objectives are dedicated to ensure the reliability of the network. Sirsant & Reddy (2020) performed a thorough analysis of the various RSMs and proposed a Combined Entropy Network Resilience (CERI) index, which was reported to be functioning satisfactorily for the cases of hydraulic and mechanical reliabilities. The approach is a simplification as it combines two objective functions into one, which is a weighted normalized sum of entropy and resiliency.. The present study, therefore, employs CERI as a substitute for reliability for performing multi-objective design of WDNs.

Several multi-objective EAs were employed to solve the WDN design problem such as Multi-Objective Genetic Algorithm (MOGA) (Johns et al., 2019; Prasad & Park, 2004), Multi-Objective Particle Swarm Optimization (Montalvo et al., 2010; Torkomany et al., 2021), Non-dominated Sorting Genetic Algorithm-II (NSGA-II) (Artina et al., 2011; Zheng et al., 2016), Clustered Non-dominated Archiving Ant Colony Optimization (Clustered-NA-ACO) (Mehzad et al., 2020), Pareto navigator technique (Moazeni & Khazaei, 2021) etc. Chaos theory has been employed in several past studies to enhance the performance of the various optimization models such as chaos GA (Yang et al., 2008; Gharooni-fard et al., 2010; Xie et al., 2016), Multi-Objective Differential Evolution-Chaos Shuffled Frog Leaping Algorithm (MODE-CSFLA) (Fang et al., 2018), chaotic PSO (Li et al., 2021). The chaotic versions of the optimization techniques have generally proved to be performing better in terms of faster convergence than the basic versions of these tools. The chaotic sequence majorly prevents the algorithm from getting trapped into the local optima. Therefore, in the present study, a chaotic version of the MOSADE algorithm is proposed and tested.

Another issue with the MOSADE algorithm is the generation of random numbers for performing mutation operation. The algorithm randomly generates a set of population members for performing the mutation operation at each stage. The previous versions of the model use randomly generated population members at each iteration. Few past studies have employed Sobol sequence for generating random numbers, which is a type of Quasi-random sequence (QRS). QRS are basically random numbers with partial randomness. The Sobol random sequences cover the search space more evenly than the pseudo random numbers. The use of QRS for performing mutation operation is found to be better than pseudo random sequence in PSO (Pant et al., 2008; Wannakarn et al., 2010). Thus, in the present study, we employ Sobol sequences for random generation of population members for carrying out mutation operation.

Consideration of the environmental aspect in designing the WDNs has emerged as important issue in the past few years. Several studies incorporated reduction of GHG emissions as one of the objectives in the optimization framework so as to arrive at sustainable design solutions (Wu et al., 2010, 2013, Lee et al., 2018). Zhang et al. (2021) presented a review on the GHG emissions associated with water and wastewater systems. It was found that electricity consumption is the largest source of GHG emissions for water systems. Additionally, the use of secondary/auxiliary pumps for supplying water to high rise buildings constituted the major source of emissions in water distribution networks. They suggested that optimal pressure management comprising of an efficient pressure management system should be prioritized so as to achieve sustainable design solutions. Therefore, reduction of GHG emissions due to pumping is considered in the present study.

Also, few studies have suggested that consideration of life cycle cost (LCC) is essential in the design formulation rather than only the cost of pipes (Jayaram & Srinivasan, 2008; Piratla et al., 2012). Liu et al. (2020) presented life cycle operation resilience assessment of WDNs and found that replacing the burst pipes with new ones improves the operational resilience. Thus, it is essential to consider the LCC, which reduces the overall capital and operational cost as well as assist with the accounting of different failures and the expenses associated with them. WDNs are also prone to future changes such as population variations, urban sprawl, change in climatic and seasonal hydro-meteorological parameters etc. (Tsegaye et al., 2020; Sirsant & Reddy, 2021). Several studies presented different expansion strategies to ensure satisfactory performance of the WDNs considering these future changes, such as phased expansion method (Creaco et al., 2014b), flexible WDN expansion method Basupi & Kapelan, 2015), MOSADE-DP method (Sirsant & Reddy, 2021), GA based Flexibility Optimization (GAFO) method (Tsegaye et al., 2020). Past studies reveal that consideration of the future changes in advance while planning the expansions is essential for an optimal solution.

The present study thus proposes a novel Chaotic Sobol Sequence based Multi-Objective Self-Adaptive Differential Evolution (CS-MOSADE) algorithm for the multi-objective design and expansion of WDNs considering the aspects of cost, reliability and GHG emissions. The proposed CS-MOSADE algorithm is an improved multi-objective version of the SADE algorithm (Qin & Suganthan, 2005), employing non-dominated sorting (Deb et al., 2002) for generation of Pareto fronts with two new improvements: (1) use of chaos theory for initial population generation and (2) use of Sobol sequences for generation of random numbers required in the mutation operation. The specific objectives of the current study are (1) to present and evaluate the performance of CS-MOSADE algorithm by comparing it with the results of well-established algorithms such as MOSADE and NSGA-II, and (2) to apply the CS-MOSADE algorithm for cost minimization, reliability maximization and GHG emissions minimization on a real WDN and evaluate the benefits compared to optimization against only cost and reliability.

Thus, the current study tries to answer the following research questions, (1) Would CS-MOSADE algorithm reduce the computational time needed to arrive to the optimal solutions, if so what % reduction in computational time and closeness to the true optimal solutions are achieved, (2) What differences, if any, would adding the reduction in GHG emissions as a third objective make in the obtained solutions.

## 2. Methods

The problem formulation for multi-objective design of WDNs is presented first, which requires minimizing the LCC, maximizing reliability, and minimizing GHG emissions. The method for estimation of LCC is presented thereafter, which requires estimation of break rate of pipes. CERI is used as a surrogate to reliability, the details of which are presented after that, followed by the method for estimation of GHG emissions. The optimization techniques adopted in the study, i.e., MOSADE, CS-MOSADE and NSGA-II are explained thereafter, followed by the metrics for performance comparison of the multi-objective optimization techniques. The overall methodology adopted in the present study is presented in Fig. 1.

### 2.1. Problem formulation

The mathematical framework for the optimization model can be represented as below

$$\text{MinimizeLCC} \tag{1}$$

$$\text{MaximizeReliability} \tag{2}$$

$$\text{MinimizeGHGemissions} \tag{3}$$

Subject to:

$$HD \ \geq H_{min}(forallnodes) \tag{4}$$

$$\sum HL_i - \sum E_p = 0 \ (forallloops) \tag{5}$$

$$\sum Q_{in} - \sum Q_{out} = 0(forallnodes) \tag{6}$$

with

$$HL_j = \frac{10.68 Q_j^{1.85} L_j}{C_{HW}^{1.85} D_j^{4.87}} \tag{7}$$

And

$$Q_j = \frac{\pi}{4} D_j^2 V_j \tag{8}$$

Here, Eq. (4) represents the minimum head requirement for different nodes, Eq. (5) represents the loop head loss, Eq. (6) represents the conservation of mass condition, Eq. (7) is the Hazen William's equation for calculation of head loss, and Eq. (8) is for flow calculation. where, $D_j$ *and* $L_j$ represent the diameter and length of link $j$ respectively, $HD$ represents the head, $H_{min}$ represents the minimum desired head at any junction, $HL$ corresponds to the head loss for a pipe, $E_p$ is the energy added by the pump, $Q_{in}$ and $Q_{out}$ correspond to the discharges flowing towards and away from a node respectively, $C_{HW}$ is the Hazen-William's roughness coefficient, and $V$ is the velocity of flow in a particular pipe. The variables in Eq. (7) stated above for head loss calculation should be in SI units, i.e., diameter, length and head in meters, and discharge in $m^3$/s. The current study uses CERI as a substitute for reliability for designing the WDNs.

#### 2.1.1. Estimating life cycle costs

The present study considers LCC as the initial installation cost ($IC$) and the break cost ($BC$, which includes repair and replacement costs) (Loganathan et al., 2002)

$$LCC = IC + BC \tag{9}$$

The consideration of LCC is particularly necessary when considering the expansions, where parallel pipes are added in stages, and it becomes essential to consider the present value of all expansions as well as break repair and replacement costs.

The IC can be calculated as a function of length and diameter of pipes using

$$IC = \sum_{j=1}^{n_p} f(D_j) L_j \tag{10}$$

The break cost can be calculated as below

$$BC = \sum_{j=1}^{n_p} BR(j) + RC(j) + AR(j) \tag{11}$$

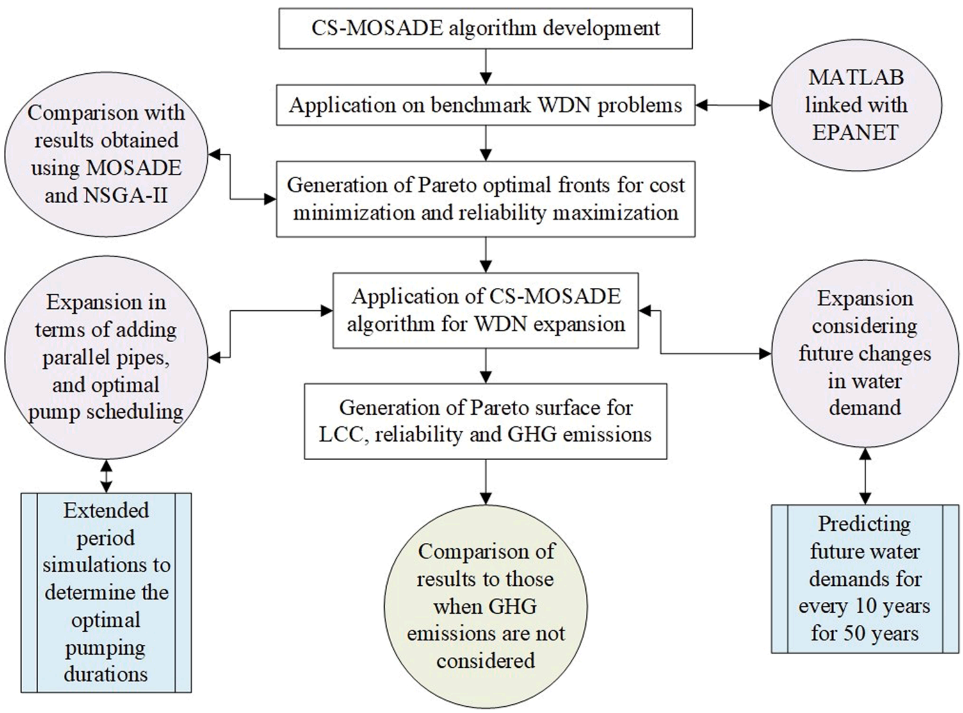


**Fig. 1.** Overall framework.

The first component, *BR*, represents the break repair cost, i.e., the cost for repairing the broken pipes; *RC* corresponds to the replacement cost, which is the cost for replacing a pipe with a new one (as the break rate has reached the threshold value, when it will be more economical to replace the pipe with a new one than to repair it); and *AR* represents the repair cost for any repairs after all the replacements of the *j*th pipe are made within the planning horizon (i.e. after k(j) replacements are done, the cost for repairs to be done for the years [k(j). s(j) +1] till the end of the planning horizon). Eqs. (12)–(14) were used to calculate the present value of the break repair and replacement costs, as the parallel pipes are added in stages (Loganathan et al., 2002).

$$BR(j) = \begin{cases} \sum_{m=1}^{k(j)} \sum_{r=1}^{s(j)} \left[ \frac{1}{(1+I)^{((m-1)s(j))+r}} . N_{D_j} . e^{A((m-1)s(j))+r} . B_{D_j} . L_j \right], if k(j) \geq 1 \\ 0, otherwise \end{cases} \tag{12}$$

$$RC(j) = \begin{cases} \sum_{m=1}^{k(j)} \frac{1}{(1+I)^{m.s(j)}} . R_{D_j} . L_j, if k(j) \geq 1 \\ 0, otherwise \end{cases} \tag{13}$$

$$AR(j) = \sum_{r=k(j)s(j)+1}^{y} \left[ \frac{1}{(1+I)^r} . N_{D_j} . e^{A(r-k(j)s(j))} B_{D_j} . L_j \right] \tag{14}$$

In the above equations, *s(j)* is the service life of pipe *j, I* represents the discount rate per year, $N_{Dj}$ represents the number of breaks per year per unit length for links having diameter $D_j$, $B_{Dj}$ represents the repair cost per break for links having diameter $D_j$, *A* represents the break growth rate coefficient per year, $R_{Dj}$ represents the replacement cost per unit length for links having diameter $D_j$. The values of $BD_j$, $RD_j$ and *A* were taken from a past study by Loganathan et al. (2002). *y* represents the design period, and *k(j)* represents the number of times link *j* needs to be replaced during the entire planning horizon and is given by

$$k(j) = \mathrm{int}\left(\frac{y}{s(j)}\right) \tag{15}$$

### 2.1.2. *Estimating break rate and service life of pipes*

The breakage of pipes is assumed to grow exponentially with time following the equation given below, to account for the ageing and other factors that may lead to an increase in the future break rate of pipes (Shamir & Howard, 1981).

$$N(t) = N(t_0).e^{(A(t-t_0))} \tag{16}$$

where *N(t)* represents the number of breaks per year per unit length for time *t*, $N(t_0)$ represents the number of breaks per year per unit length at time $t=t_0$, and *A* is the growth rate coefficient per year.

As can be seen from the above equation, the number of breaks will increase with time, and after a certain period, the break repair cost will be so high that replacement will be economical. The break rate at which replacement needs to be done is termed as the threshold break rate and can be estimated using the following equation (Loganathan et al., 2002).

$$BR_{th} = \frac{\ln(1+I)}{\ln\left(1+\frac{CR}{L_j}\right)} \tag{17}$$

where *CR* is the cost ratio which is equal to ($C_{repair}/C_{replace}$) and is expressed as a function of diameter, such that they follow a linear relationship as $CR = pD+q$, where *p* and *q* are the regression coefficients and *D* is the diameter in mm, *I* is the discount rate per year and $L_j$ is the length of *j*th link. As per the study by Suribabu & Neelakantan (2006), the values of *p* and *q* are taken as $p = 0.0048$ and $q = 6.6805$, so that $CR = 0.0048\ D + 6.6805$. The estimation of threshold break rate is particularly useful to find out the break rate at which the pipe needs replacement, and consequently the total number of replacements of a particular pipe throughout the planning horizon.

Substituting the value of the threshold break rate as *N(t)* in the Eq. (6), $t_0$ as 0 and *t* as *s* (service life of pipe), it leads to

$$s = \frac{1}{A}\ln\left(\frac{BR_{th}}{N_0}\right) \tag{18}$$

The estimation of service life of a pipe will ultimately aid in determining the number of times the pipe needs replacement during the entire planning horizon, as presented in Eq. (15).

### 2.1.3. Combined entropy-resiliency index (CERI)

CERI is estimated as the weighted normalised sum of entropy and resiliency (Sirsant & Reddy, 2020).

$$CERI = w_1.(S/S_{\max}) + w_2.(I_r/I_{r,\max}) \tag{19}$$

where, $S$ and $S_{max}$ are the entropy and maximum entropy respectively for a WDN, $I_r$ and $I_{r,max}$ are the resiliency and maximum resiliency respectively, $w_1$ and $w_2$ are the weights assigned for entropy and resiliency respectively. $S_{max}$ was calculated by considering that all paths supplying water to a demand node carry equal flow, thus the total flow in a link will be equal to the summation of all the flows in the path. More details about estimation of maximum entropy flows can be found in Tanyimboh & Templeman (1993). On the other hand, the value of $I_{max}$ is always set to 1 (Todini, 2000). The values of $w_1$ and $w_2$ are such that they vary between 0 and 1 and their summation equals 1. As suggested by Sirsant & Reddy (2020), the value of $w_1$ and $w_2$ are adopted as 0.4 and 0.6 respectively.

Entropy is defined as the measure of the degree of uncertainty depicted by a probability distribution (Shannon, 1948). As a result, a solution with a greater entropy makes fewer assumptions about the system and the accompanying uncertainties. For the case of WDN design, the uncertainties comprise of random demands, random component failure, unpredictable fluctuations in terms of firefighting demands, etc. As per the notion of entropy, a probability distribution of flow values with a greater entropy assumes fewer uncertainties and can thus manage them more robustly. As a result, solutions with a larger entropy should be more reliable. The following equation is adopted in the study for estimation of entropy (Tanyimboh & Templeman, 1993)

$$S = S_o + \sum_{j=1}^{N} P_j S_j \tag{20}$$

where, $S_o$ is the entropy because of multiple supply sources, $S_j$ is the entropy for $j$th demand node, for $j$ varying from 1 to $N$, where $N$ being the number of demand nodes, and $P_j$ is the percentage of total flow that reaches $j$th node and is estimated as

$$P_j = \frac{T_j}{T} \tag{21}$$

where, $T_j$ is the total flow reaching $j$th node, and $T$ corresponds to the entire network's total flow and is equal to the summation of nodal demands.

The terms $S_0$ and $S_i$ are estimated as follows

$$S_0 = -\sum_{j \in I} p_{0j} \ln p_{0j} \tag{22}$$

$I_s$ is the set of supply sources

$$S_j = -\sum_{jk \in ND_j} p_{jk} \ln p_{jk} \tag{23}$$

where, $ND_j$ corresponds to the set of all the outflows including any demand from $j$th node, $p_{jk}$ is the fraction of total outflow $T_j$ including any demand from $j$th node

$$P_{jk} = \frac{q_{jk}}{T_j} \tag{24}$$

where, $q_{jk}$ is the outflow for link $jk$.

On substituting all the above values in Eq. (20), the following equation is obtained

$$S = -\sum_{j \in I_s} p_{0j} \ln p_{0j} + \sum_{j=1}^{N} \frac{T_j}{T_0} \left[ -\sum_{jk \in ND_j} p_{jk} \ln p_{jk} \right] \tag{25}$$

The other term used in CERI estimation is resiliency Proposed by Todini (2000). Calculating resiliency involves estimation of available energy from the sources as well as internal energy dissipation in the system. Maximizing resiliency means maximizing the energy available for internal dissipation in case of sudden failure. There are various improved formulations available in the literature to estimate the resilience of a water network, such as modified resilience index (Jayaram & Srinivasan, 2008), the pressure driven variant of resilience index also termed as the Generalized resilience/failure (GRF) index (Creaco et al., 2016). .The advantage of the GRF index is that it can be used effectively for pressure driven analysis, which is the preferred modelling approach, especially for pressure deficient conditions such as pipe breakage, demand fluctuations, leakages etc. The GRF is estimated as the summation of resilience index and failure index which are described below.

The resilience index is calculated as

$$I_r = \frac{\max(q_{user} H - d.H_{des}, 0)}{Q_0 H_0 + Q_P H_P - d.H_{des}} \tag{26}$$

where, $q_{user}$ is the actual flow delivered to the user, estimated using the formulation proposed by Wagner et al. (1988) for pressure driven analysis, $H$ is the actual head at the nodes, d is the desired flow for different nodes, $H_{des}$ is the minimum desired head at different nodes, $Q_0$ is the outflow from the supply sources, $H_0$ is the head at the supply source, $Q_p$ is the flow through pumps, $H_p$ is the additional head delivered by the pumps.

The failure index is calculated as

$$I_f = \frac{\min(q_{user} H - d.\ H_{des}, 0)}{d.H_{des}} \tag{27}$$

The GRF was then calculated as proposed by Creaco et al. (2016)

$$GRF = I_r + I_f \tag{28}$$

However, in the present study, the solutions with negative values of $I_r$ were discarded by the optimization algorithm, by using a penalty function, as they represent less redundant solutions, and thus are considered as infeasible.

### 2.1.4 Estimation of green house gas emissions

The emissions related to the energy consumption due to operation of the pumps is included in the present study. The GHG emission due to pumping can be estimated as (Wu et al., 2010)

$$GHG = EF[AEC] \tag{29}$$

where, $EF$ is the emission factor, $AEC$ is the annual electricity consumption in kWh. In the present study, an $EF$ value of 0.598 is adopted for UAE, as per the recommendation of Ji et al. (2016). Even though the UAE is planning to rely more on green energy (Alzaabi & Mezher, 2021), which would result in lower GHGs for the energy consumed, the authors assumed that this would be offset by the higher impact of lower GHG emissions in the future (Weisser, 2007). Thus, the EF was assumed constant for the planning period.

## 2.2. Optimization techniques

The present study proposes an improved Chaotic Sobol Sequence based MOSADE algorithm. The details of the MOSADE algorithm are presented first, followed by the improved version proposed in the present study. The results are compared with the ones obtained by the NSGA-II algorithm, the details of which are presented thereafter.

### 2.2.1. MOSADE algorithm

The MOSADE algorithm involves multi-objective version of SADE algorithm by combining the Parent and Child vectors and forwarding the top Pop (population size) vectors to the next iteration. The steps involved in the MOSADE algorithm are as follows

(1) Initialization of parameters of the algorithm such as the population size (*Pop*), maximum number of iterations ($I_{max}$) and mutation and crossover factors mean values ($F_m$ and $CR_m$)
(2) Initialize the starting population (called the target vector) depending on the upper and lower bounds of the decision variable. Estimate the value of the objective function for each solution.
(3) For each population member, mutation and crossover factor values are generated, by considering them to follow a normal distribution having mean $F_m$ and $CR_m$ and standard deviation of ($\sigma_F$ and $\sigma_{CR}$ ) of 0.3 and 0.1 respectively.
(4) (4) Mutation is performed on each population member which formulates the mutant vector using the following equation

$$V_{i,G} = X_{r_1,G} + F_i\left(X_{r_2,G} - X_{r_3,G}\right) \tag{30}$$

where $V_{i,G} = [v_{1,i,G}, v_{2,i,G}, \ldots, v_{D,i,G}]$ is a mutant vector associated with population member *i* and generation *G*; $X_{r1,G}$, $X_{r2,G}$ and $X_{r3,G}$ are three randomly chosen population vectors from the current generation; and $F_i$ is the mutation factor for population member *i*. The purpose of mutation is to generate new vectors, which is a combination of the features of old vectors.
(5) Crossover is performed to formulate the trial vector using the following rule,

$$u_{j,i,G} = \begin{cases} v_{j,i,G}, if\left(rand_j[0,1] \le CRor(j = j_{rand}\right) \\ x_{j,i,G}, otherwise \end{cases} \tag{31}$$

where $U_{i,G} = [u_{1,i,G}, u_{2,i,G}, \ldots, u_{D,i,G}]$ is *i*th trial vector at generation *G;* $u_{j,i,G}$ is the *j*th decision variable for *i*th member at generation G; $rand_j$ is a random value between 0 to 1 for each dimension of the vector; and $j_{rand}$ is a random number from 1 to *D*, the dimension of each vector. The purpose of performing crossover is to randomly change a decision variable in the mutant vector so that the target vector and the mutant vector are not the same.
(6) Calculate the values of the objective function for the trial vector that was produced.
(7) Repeat steps 4 to 6 for each population member.
(8) Combine the trial and target vectors and extract the top NP solutions by conducting non-dominated sorting and crowding distance calculations as performed in NSGA-II (Deb et al., 2002).
(9) Based on the successful values of the mutation and crossover factors for the previous 10 iterations, update the values of $F_m$ and $CR_m$ after every 10 iterations, and build a new set of these factors for each member of the population using the updated $F_m$ and $CR_m$ values, as stated in step (3) above. Any combination of mutation and crossover parameters is regarded successful if the offspring produced by this combination formulates a fitter or non-dominated solution than the parent vector.
(10) The procedure is continued until all the termination criteria have been met. The 'maximum number of iterations' is used as the termination criteria in this investigation.

### 2.2.2. CS-MOSADE algorithm

In the CS-MOSADE algorithm, the chaotic sequence is employed for population initialization, instead of random population initialization. Chaos can be understood as unsettling or order without predictability. They occur in deterministic non-linear systems which are unpredictable in nature. Employing chaotic maps for generation of initial population will lead to a large number of possible starting points, which ultimately may lead to various possible solutions on applying the optimization tool. Various kinds of chaotic maps exist such as logistic, gauss, sinus, sinusoidal iterator, tent map etc. Özer & Ertokatlı (2010) analysed various chaotic maps and found the sinus map to be the most efficient in improving the quality of solutions. Thus, in the present study, sinus map is employed which is represented by the following equation (Özer & Ertokatlı, 2010)

$$X_{n+1} = 2.3(X_n)^{2\sin(\pi X_n)} \tag{32}$$

where, $X_{n+1}$ represents the (n+1)$^{th}$ term of the sequence, which is a function of $X_n$, the *n*th term. The behaviour of the sinus map for different starting values (i.e. $X_n$) of 0.5, 1, 2 and 3 is shown in Fig. 2. It can be seen that the chaotic behaviour of the sinus map is irrespective of the initial value. Also, it covers a wide range of values, which will ultimately ensure the initial population generation covers an extensive range and variation of solutions.

Another improvement made in the MOSADE algorithm is the employment of Sobol sequence for generating random numbers for mutation operation. Sobol sequence is a type of quasi random sequence (QRS) with less discrepancy compared to the pseudorandom sequence. If the fraction of points in a sequence belonging to a random set *A* is near to proportionate to the measure of *A*, the discrepancy of the sequence is said to be low. The QRS are deemed to be more efficient that pseudorandom sequence because of their ability to explore the search space more evenly than the pseudorandom sequence (Chi et al., 2005). As a result, utilizing the Sobol sequence to generate random numbers will result in a more balanced exploration of the search space. Details regarding formation of the Sobol sequences can be accessed in Pant et al. (2008).

As a result, instead of entirely random production of population members, the three arbitrarily chosen population vectors $X_{r1,G}$, $X_{r2,G}$, and $X_{r3,G}$ utilized in Eq. (28) are created using Sobol sequences in this study. For each dimension, a 3-dimensional Sobol sequence is formed, with random points equal to the population size utilized in the MOSADE method. Following that, the random numbers are scaled from 1 to population size. To preserve variation in the population vectors picked for a single population member at various runs, a pseudo random number generator is employed to shuffle the rows of the size (population size x 3) matrix of the random numbers created. The steps involved in the CS-MOSADE algorithm are presented in Fig. 3.

### 2.2.3. NSGA-II algorithm

The NSGA-II method, developed by Deb et al. (2002), is a multi-objective evolutionary algorithm that employs non-domination sorting and crowding distance computations to perform the basic processes of population generation, selection, crossover, mutation, and formulation of the new population. Tournament selection, simulated binary crossover, and polynomial mutation are employed in this study. Deb et al. (2002) provided a thorough description of the procedures necessary in implementing the NSGA-II algorithm.

## 2.3. Performance metrics

Four metrics for performance evaluation of multi-objective evolutionary algorithms from the literature are employed in the present study, namely, Inverted generational distance, Spacing metric, Hyper-volume, and Coverage function.

### 2.3.1. Inverted generational distance (IGD)

The IGD metric, developed by van Veldhuizen & Lamont (1999), calculates the distance between the members of the derived non-dominated set of solutions and the actual Pareto-optimal front. IGD (A, P) can be calculated as:

$$IGD(A,P) = \frac{\sum_{\tau \in P} d(\tau, A)}{|P|} \tag{33}$$

where *P* is the true Pareto-optimal vector set, *A* is the acquired non-dominated set of solutions, and *d (τ, A)* is the Euclidian distance between the elements of *P* to its nearest member in *A*. Therefore, the smaller the value of IGD, the closer it gets to the genuine Pareto-optimal

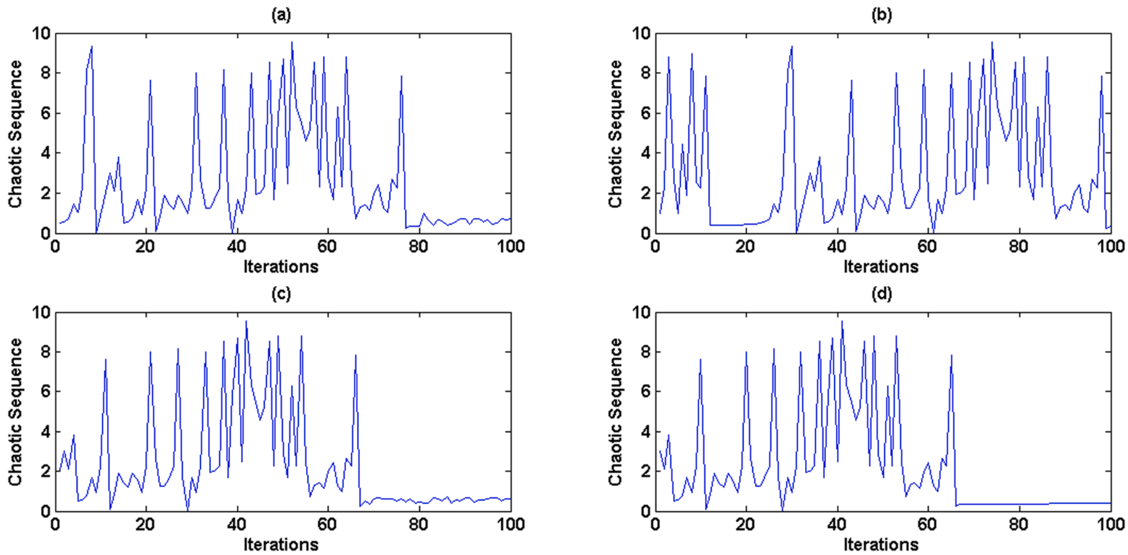


**Fig. 2.** Chaotic behaviour of sinus map for initial value of (a) 0.5 (b) 1 (c) 2 and (d) 3.

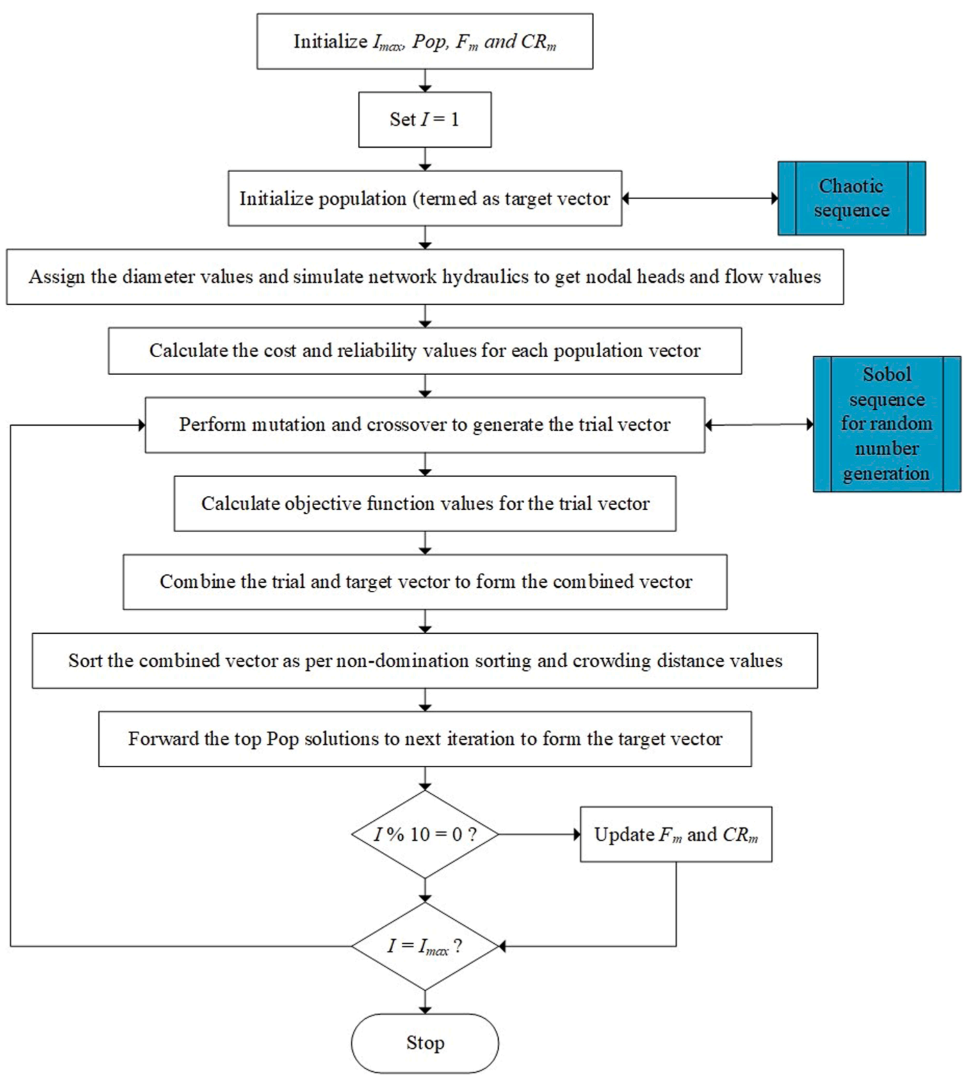


**Fig. 3.** Steps involved in CS-MOSADE algorithm.

front, with 0 signifying absolute convergence. Faster convergence of an algorithm is depicted by fast convergence of the IGD value towards 0, which indicates the time required to reach an optimal WDS design. The IGD values are used in the present study to determine the number of function evaluations needed for different optimization problems, presented in Section 4.1. Similarly, the number of function evaluations needed for each WDN problem are found by determining the number of iterations at which IGD converges to zero, as discussed in Section 4.3.

#### 2.3.2. Spacing metric

Schott & Jason (1995) formulated a metric to measure the spacing and uniformity among the derived non-dominated solutions and can be calculated employing the following equation

$$S = \sqrt{\frac{1}{|Q|}\sum_{i=1}^{|Q|}(d_i - \overline{d})^2} \tag{34}$$

where $Q$ is the Pareto-optimal solutions set obtained and $d_i$ is the distance measure which is the minimum value of the sum of absolute difference in objective function values between $i$th solution and any other solution acquired in the non-dominated set can be calculated as

$$d_i = \min\left\{\sum_{m=1}^{M}\left|f_m^i - f_m^k\right|\right\}\forall k = 1,2,3, Nand k \neq i \tag{35}$$

here $f_m^i$ represents the $m$th objective function value of $i$th solution, $M$ is the number of objectives, $k$ takes the values from 1 to $N$ (the number of non-dominated solutions obtained) except $i$, and $\overline{d}$is the mean value of the above distance measure.

Smaller value of spacing metric represents better performance of the algorithm. Thus, spacing metric is considered as a measure of the quality of Pareto-optimal solutions in terms of even distribution in the Pareto-optimal front. Thus, smaller spacing metric indicates a Pareto front with more evenly distributed solutions, and thus the uniform coverage of the solutions in the Pareto-front by the algorithm. The spacing metric values are presented in Section 4.3 to compare the relative uniformity in the Pareto fronts obtained for different WDN problems solved using different algorithms.

#### 2.3.3. Hyper-volume/hyper-area

This metric developed by van Veldhuizen & Lamont (1999), estimates the volume in objective space covered by the members of the Pareto-optimal front, with regard to the worst solution, for problems where all objectives are to be minimized. It is estimated by calculating the summation of all the hyper-cubes of solution $i \epsilon Q$, estimated with respect to a chosen worst solution $W$, with the solution $i$ as the diagonal corners of the hyper-cube. Similar to the computation of HV, the union of all hyper-rectangles, referred to as Hyper-area (HA), is employed in the case of two-objective optimization. Thus, if $a_i$ represents the hyper-rectangle estimated for solution $i$, then the Hyper-area (HA) is obtained as

$$HA = area\left(\bigcup_{i=1}^{|Q|} a_i\right) \tag{36}$$

Normalisation of the objective function values is required for estimating HV/HA, else it would lead to misleading values. Larger the value of HA for an algorithm better is its performance compared to another algorithm with smaller value for a particular problem. Therefore, HA is a measure of the extent of convergence of the algorithm towards the true Pareto-optimal front, indicating how close is the obtained Pareto-front to the true Pareto front. HA values are presented in Sections 4.1 and 4.3 to compare the convergence of different algorithms towards true Pareto-optimal front for different WDN problems.

#### 2.3.4. Coverage function

Introduced by Zitzler & Thiele (1998), the coverage function (CF) can be used as a means to evaluate the performance of two algorithms leading to Pareto-optimal sets, say $P$ and $Q$, and is determined by estimating the proportion of solutions in $Q$ which are weakly dominated by the solutions in $P$. The objective functions of the solutions in $P$ should not be poorer than the corresponding objective functions of the solutions in $Q$, for a given solution in $P$ to be considered weakly dominating a particular solution in $Q$. Each solution in $Q$ must be weakly dominated by at least one solution in $P$ for the solution set $P$ to weakly dominate the set $Q$. Thus,

$$C(P,Q) = \frac{|\{q \in Q | \exists p \in P : p \geq q\}|}{|Q|} \tag{37}$$

Therefore, CF is a measure of the relative convergence of one algorithm over another towards the true Pareto-optimal front. Hence, CF can be used as an indicator of how well an algorithm converges compared to another. CF values are presented in Section 4.3 to compare the relative convergence of one algorithm over another for different WDN problems.

### 2.4. WDN expansion incorporating future changes in water demand

Expansions are planned for WDNs considering the future changes in water demand in terms of adding parallel pipes to the existing pipes at different stages, such that the LCC of all the expansions is minimum, as well as the minimum reliability (out of all stages) is maximum. Further, the optimal scheduling of pumps is performed considering extended period simulations (EPS) such that the total GHG emissions due to electricity consumption is minimum.

Thus, the overall problem formulation comprises of determination of parallel pipes to be added at different stages as well as optimal pump scheduling so as to achieve the minimum LCC, maximum reliability and minimum GHG emissions. The solution methodology comprises of determination of size, location and time of the parallel pipes to be added such that LCC is minimum and reliability is maximum; as well as the optimal hours of operation of pump(s) such that the GHG emissions are minimum.

## 3. Case studies of WDNs

The CS-MOSADE algorithm was first applied and tested on two benchmark WDN problems, Two loop and GoYang WDNs. The Two loop WDN comprises of 8 links, 6 junctions, and a supply source supplying water by gravity at a fixed head of 210 m (Alperovits & Shamir, 1977). There are 14 available pipe diameters ranging from 25.4 to 609.6 mm.

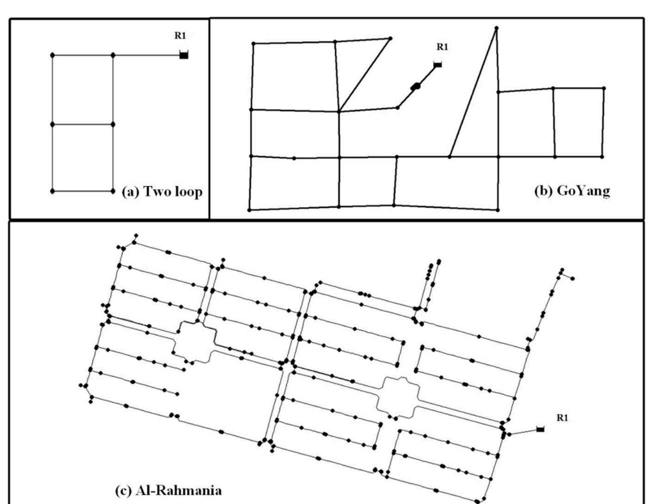


**Fig. 4.** Layout of (a) Two loop (b) GoYang and (c) Al-Rahmania WDNs. (Here R1 depicts the reservoir).

All the pipes have a fixed length of 1000 m having a $C_{HW}$ value of 130. The layout of Two loop WDN is shown in Fig. 4(a). GoYang WDN is a medium sized WDN comprising of 30 links and 22 junctions, a pump of constant power of 4.52 kWh, and a supply source at a static head of 71 m. The layout of GoYang WDN is shown in Fig. 4(b). There are 8 available pipe diameters ranging from 80 to 350 mm. The pipes have a roughness coefficient $C_{HW}$ value of 100. More details about the GoYang WDN can be found in Kim et al. (1994).

The CS-MOSADE algorithm is then applied on a real WDN of Al-Rahmania zone, located in Sharjah, UAE. The WDN comprises of 339 pipes, 395 nodes, and a reservoir at a fixed head of 237.27 m. The pipes are made of riveted steel having $C_{HW}$ of 100. There are 12 available pipe diameters ranging from 150 mm to 650 mm, with their unit costs varying from 165.36 AED to 498.07 AED. The layout of Al-Rahmania WDN is presented in Fig. 4(c).

The water demand is assumed to grow exponentially, as per the following equation

$$D_T = D * \left(1 + \frac{R}{100}\right)^T \tag{38}$$

where, $D_T$ represents the demand at time period *T, D* is the demand at the beginning of planning horizon and $R$ is the annual rate of increase of demand. $R$ is considered as 3 in the present study.

## 4. Results

First the CS-MOSADE algorithm is validated by application on nine constrained test problems for multi-objective optimization. Thereafter, the CS-MOSADE algorithm is applied and tested on two benchmark WDNs, the Two loop and GoYang, followed by the application to a real WDN (Al-Rahmaniya). The results are compared with those obtained using MOSADE and NSGA-II algorithms. The performance comparison of the three algorithms is presented. The CS-MOSADE algorithm is then applied for optimal pump scheduling and expansion of WDNs considering the objectives of minimizing the LCC, maximizing the reliability and minimizing the GHG emissions. The results are compared to those when only the objectives of LCC minimization and reliability maximization are considered. The comparison is important to elucidate whether or not the inclusion of GHG minimization as an objective in the optimization problem had an impact on the outcomes.

### 4.1. Validating the performance of CS-MOSADE

In this study the CS-MOSADE algorithm was first applied on nine constrained test problems for multi-objective optimization. The results were compared to those obtained in past studies (Datta & Regis, 2016; Peng et al., 2017; Yang et al., 2019). The BHN, SRN and TNK test problems comprise of 2 decision variables and 2 objective functions each. CF1, CF2 and CF3 comprise of 2 objectives and 10 decision variables. NCT1, NCT2 and NCT3 comprise of 2 objectives and 30 decision variable each. The comparisons are presented in Table 1. The values of the IGD and HV obtained in the present study, are better in all the cases compared to the past studies. Although the improvement in the values of the performance metric is small, since the problems are benchmark test functions, even a small improvement can be considered significant. This implies that the CS-MOSADE algorithm has faster and higher convergence towards the absolute Pareto-optimal solutions. It is evident that the improvement is more pronounced as the number of decision variables increases. This indicates that the performance of the CS-MOSADE algorithm is more suitable for problems with a moderate number of decision variables.

### 4.2. Obtained Pareto-optimal fronts

The Pareto-optimal fronts obtained for the three WDN problems is presented in Fig. 5. The results are presented by combining the solutions obtained for 20 independent runs for each algorithm. The population size is chosen as 200 for Two loop, 300 for GoYang and 3500 for Al-Rahmaniya WDN, after performing some preliminary analysis, for a maximum iteration of 1000 for Two loop and GoYang and 5000 for Al-Rahmaniya WDN as suggested by past studies (Keedwell & Khu, 2006, Monsef et al., 2019). The number of iterations is kept large enough so as to ensure that convergence to true Pareto-optimal front occurs within this chosen number of iterations. It can be observed that all three algorithms lead to similar Pareto fronts. However, on close observation of Fig. 5, it can be seen that CS-MOSADE algorithm covers a wider range of solutions in terms of capturing the lowest and highest cost solutions. Comparison of a representative set of solutions obtained using the three algorithms for Two loop WDN is presented in Table 2. The solutions presented are in terms of cost and reliability values, diameter of pipes obtained, head and flow values for lowest cost and highest reliability solutions obtained using each algorithm, as well as solutions with a reliability of 0.8. From Table 2, it can be seen that both the lowest cost and highest reliability solutions obtained using CS-MOSADE algorithm are better compared to MOSADE and NSGA-II. This implies that the CS-MOSADE algorithm is covering a wider range of solutions compared to the MOSADE and NSGA-II algorithms. For example, in case of Two loop WDN, the lowest cost solution captured by CS-MOSADE and MOSADE is (419,000, 0.312), whereas that captured by NSGA-II is (436, 000, 0.413). The highest reliability solution captured by CS-MOSADE and NSGA-II is (4,020,000, 0.994), while the one captured by MOSADE is (3,100,000, 0.992). On comparing typical solutions for reliability level of 0.8, the CS-MOSADE algorithm leads to lower cost solution compared to the other algorithms. This implies that CS-MOSADE algorithm is converging better than the other two algorithms. The head and flow values for the solutions vary slightly for different nodes. For example, in case of Two loop WDN, for reliability level 0.8, the head values for the solution obtained using CS-MOSADE

**Table 1**
Performance comparison of CS-MOSADE algorithm with past studies on benchmark multi-objective test problems

| Test problem | Source | Algorithm used (in past study) | IGD | Hyper-volume | | |
|---|---|---|---|---|---|---|
| | | | Present study | Past study | Present study | Past study |
| BNH | Datta & Regis (2016) | SAES-RBF[a] | 0.0016 | - | 5065.66 | 5053.54 |
| SRN | Datta & Regis (2016) | SAES-RBF[a] | 0.0018 | - | 5094.19 | 5082.90 |
| TNK | Datta & Regis (2016) | SAES-RBF[a] | 0.0023 | - | 30198.34 | 29268.88 |
| CF1 | Peng et al. (2017) | EADC[b] | 0.0006 | 0.0008 | 3.51 | 3.47 |
| CF2 | Peng et al. (2017) | EADC[b] | 0.0015 | 0.0018 | 3.76 | 3.61 |
| CF3 | Peng et al. (2017) | EADC[b] | 0.0028 | 0.0035 | 3.35 | 3.26 |
| NCT1 | Yang et al. (2019) | MODE-SaE[c] | 0.0392 | 0.0484 | 11.27 | 11.07 |
| NCT2 | Yang et al. (2019) | MODE-SaE[c] | 0.0887 | 0.0967 | 11.32 | 11.07 |
| NCT3 | Yang et al. (2019) | MODE-SaE[c] | 0.0156 | 0.0261 | 11.55 | 11.27 |

[a] Surrogate assisted evolution strategy radial basis function,
[b] : Evolutionary algorithm with directed weights for constraint handling,
[c] : Multi-Objective differential evolution with self-adaptive epsilon

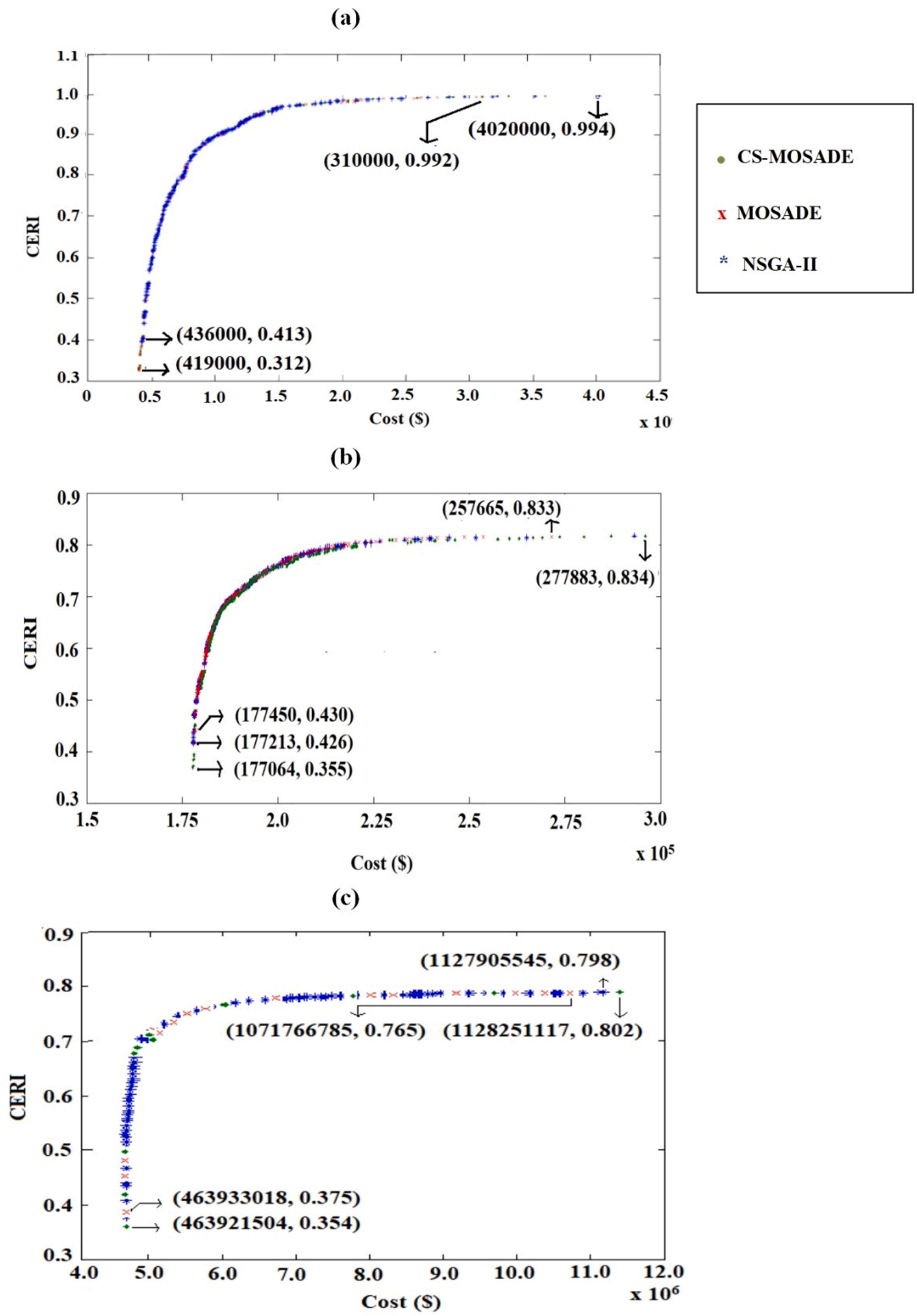


**Fig. 5.** Pareto-optimal fronts acquired through CS-MOSADE, MOSADE and NSGA-II algorithms for (a) Two loop (b) GoYang and (c) Al-Rahmaniya WDNs.

algorithm are (57.46, 45.61, 50.62, 53.83, 38.23, 41.83), for reliability value of 0.808, while the head values for the solution obtained using MOSADE are (57.46, 45.63, 50.61, 53.89, 38.11, 42.03), for reliability value of 0.809. The head values are varying since the diameter values are changing for different pipes. Thus, the solutions are hydraulically similar for similar reliability levels, but better in terms of cost for the case of CS-MOSADE algorithm.

The performance metrics of the three algorithms for all the three WDNs is presented in Table 3. It can be seen that the values of the spacing metric are the least for CS-MOSADE algorithm for all three WDN problems. This implies that the Pareto-optimal solutions obtained are the most even in case of CS-MOSADE algorithm. On comparing the HA values, the CS-MOSADE algorithm leads to the largest values of HA. This implies that the Pareto fronts are converged to the highest extent in case of CS-MOSADE algorithm. The values of CF for the three algorithms shows that the highest values are obtained for S(CSM,N) which means that the highest percentage of solutions of NSGA-II are being weakly dominated by one or more solutions of the CS-MOSADE algorithm. While the values of S(M,CSM) and S(N,CSM) are very less. This means that very less percentage of solutions acquired through CS-MOSADE algorithm are weakly dominated by one or more solutions obtained using MOSADE and NSGA-II algorithms. Thus, considering the three-performance metrics it can be seen that CS-MOSADE algorithm performs better than MOSADE and NSGA-II algorithms in terms of even distribution of solutions, convergence towards true Pareto-optimal front and percentage of solutions that dominate the solutions obtained using

**Table 2**
Comparison of a representative set of solutions for two loop WDN obtained using different optimization algorithms.

| Solution Type | Algorithm | Solution (Cost ($), CERI) | Diameter of pipes (mm) | Head values at nodes (m) | Flow in pipes ($m^3$/h) |
|---|---|---|---|---|---|
| Lowest cost solution | CS-MOSADE and MOSADE | (419,000, 0.312) | (457.2, 254,406.4, 101.6, 406.4, 254, 254, 25.4) | (53.25, 30.46, 43.45, 33.80, 30.44, 30.55) | (1120, 336.87, 683.13, 32.57, 530.56, 200.56, 236.87, 0.56) |
| Lowest cost solution | NSGA-II | (423,000, 0.413) | (508, 355.6, 355.6, 25.4, 304.8, 25.4, 355.6, 254) | (55.96, 39.41, 46.69, 44.83, 31.61, 29.98) | (1120, 568.83, 451.17, 0.60, 330.57, 0.57, 468.83, 199.42) |
| Highest reliability solution | CS-MOSADE and NSGA-II | (4,020,000, 0.994) | (609.6, 609.6, 609.6, 609.6, 508, 609.6, 609.6, 609.6) | (58.34, 48.01, 52.88, 57.8, 42.59, 47.63) | (1120, 461.85, 558.15, 202.04, 236.11, 93.89, 361.85, 293.89) |
| Highest reliability solution | MOSADE | (3,100,000, 0.992) | (609.6, 609.6, 609.6, 558.8, 508, 457.2, 609.6, 558.8) | (58.35, 48.01, 52.88, 57.81, 42.65, 47.67) | (1120, 463.71, 556.28, 169.47, 266.82, 63.18, 63.71, 263.18) |
| Solution with reliability 0.8 | CS-MOSADE | (752,000, 0.808) | (558.8, 355.6, 508, 355.6, 355.6, 25.4, 304.8, 304.8) | (57.46, 45.61, 50.62, 53.83, 38.23, 41.83) | (1120, 288, 732, 282, 330, 0, 188, 200) |
| Solution with reliability 0.8 | MOSADE | (761,000, 0.809) | (558.8, 355.6, 508, 355.6, 355.6, 101.6, 304.8, 304.8) | (57.46, 45.63, 50.61, 53.89, 38.11, 42.03) | (1120, 286, 734, 276, 338, 8, 186, 192) |
| Solution with reliability 0.8 | NSGA-II | (762,000, 0.817) | (558.8, 355.6, 508, 355.6, 355.6, 25.4, 355.6, 304.8) | (57.46, 45.29, 50.73, 54.23, 38.34, 42.23) | (1120, 313, 707, 257, 330, 0, 213, 200) |

**Table 3**
Performance comparison of CS-MOSADE, MOSADE and NSGA-II algorithms for multi-objective design of WDNs, statistics presented in terms of best, worst, mean, and standard deviation (SD) values for Spacing metric, Hyper-area and Coverage function.*

| Case study | Statistic | Performance metric<br>Spacing metric<br>CS-MOSADE | MOSADE | NSGA-II | Hyper-area<br>CS-MOSADE | MOSADE | NSGA-II | Coverage function<br>S(CSM, M) | S(M, CSM) | S(CSM, N) | S(N, CSM) | S(M, N) | S(N, M) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Two loop | Best | 0.0110 | 0.0165 | 0.0168 | 1.986 | 0.763 | 0.694 | 0.4512 | 0.1875 | 0.7252 | 0.1667 | 0.5486 | 0.2041 |
| | Worst | 0.0139 | 0.0179 | 0.0185 | 1.990 | 0.546 | 0.587 | 0.2316 | 0.0612 | 0.4187 | 0.0134 | 0.2418 | 0.0781 |
| | Mean | **0.0119** | 0.0175 | 0.0165 | **1.764** | 0.645 | 0.652 | 0.3515 | 0.1153 | **0.5176** | 0.1256 | 0.3786 | 0.1418 |
| | SD | 0.0121 | 0.0098 | 0.0075 | 0.0025 | 0.0032 | 0.0321 | 0.1241 | 0.0465 | 0.2245 | 0.0332 | 0.1518 | 0.0716 |
| GoYang | Best | 0.0508 | 0.0449 | 0.0751 | 2.7142 | 2.6781 | 2.7104 | 0.2865 | 0.0516 | 0.3319 | 0.0514 | 0.2718 | 0.0414 |
| | Worst | 0.0621 | 0.0759 | 0.0803 | 2.7014 | 2.6591 | 2.6215 | 0.1681 | 0.0129 | 0.1613 | 0.0256 | 0.1701 | 0.0318 |
| | Mean | **0.0613** | 0.0775 | 0.0791 | **2.7032** | 2.6614 | 2.6771 | 0.1043 | 0.0467 | **0.2817** | 0.0589 | 0.1988 | 0.0513 |
| | SD | 0.0079 | 0.0089 | 0.0021 | 0.0005 | 0.0008 | 0.0041 | 0.0341 | 0.0086 | 0.0587 | 0.0059 | 0.0425 | 0.0089 |
| Al-Rahmania WDN | Best | 0.0285 | 0.0371 | 0.1171 | 17.338 | 17.275 | 17.018 | 0.1671 | 0.1461 | 0.1643 | 0.1541 | 0.8474 | 0.2329 |
| | Worst | 0.0426 | 0.0519 | 0.1514 | 17.185 | 17.312 | 16.841 | 0.0573 | 0.0171 | 0.0452 | 0.0264 | 0.0628 | 0.0375 |
| | Mean | **0.0385** | 0.0459 | 0.1316 | **17.561** | 17.314 | 16.987 | 0.7821 | 0.0659 | **0.8645** | 0.0754 | 0.8137 | 0.0778 |
| | SD | 0.0067 | 0.0071 | 0.0136 | 0.0118 | 0.0119 | 0.0641 | 0.2231 | 0.1366 | 0.3167 | 0.1428 | 0.2651 | 0.1279 |

Note: In S(CSM,M), CSM=CS-MOSADE and M=MOSADE, and in S(CSM,N), N=NSGA-II.
Bold numbers indicate the best performing algorithm.
* The results are obtained by 20 independent runs for both algorithms.

other algorithms.

### 4.3. Solution convergence for different algorithms

For Two loop WDN, considering a population size of 200, the CS-MOSADE, MOSADE and NSGA-II algorithms converged at 275, 580 and 800 solutions respectively. Thus, the number of function evaluations needed is around 55,000, 116,000 and 160,000 for CS-MOSADE, MOSADE and NSGA-II algorithms, requiring around 1.92, 4.05 and 5.591 h respectively. In case of GoYang WDN, the CS-MOSADE, MOSADE and NSGA-II algorithms converged at nearly 250, 300 and 550 iterations respectively on adopting a population size of 300. The number of function evaluations thus needed is around 75,000, 90,000 and 165,000 for CS-MOSADE, MOSADE and NSGA-II algorithms, requiring a computational time of around 3.05, 6.65 and 8.91 h respectively. In case of Al-Rahmaniya WDN problem, the CS-MOSADE, MOSADE and NSGA-II algorithms converged at around 200,300 and 600 iterations for a population size of 3500, thus requiring 700,000, 1,050,000 and 2,100,000 number of function evaluations. The computational time needed is around 30.45, 60.67 and 80.78 h for CS-MOSADE, MOSADE and NSGA-II algorithms. Thus, it can be concluded that the computational time in case of CS-MOSADE algorithm is reduced by around half compared to MOSADE algorithm, and by one third compared to NSGA-II algorithm. The main reason for faster convergence of the CS-MOSADE algorithm as compared to the other algorithms is due to the incorporation of Chaotic sequence for initial population generation and Sobol Sequence for generating random numbers for performing mutation operation. The Chaotic sequence helps in maintaining a very huge variation of initial solutions, which ultimately leads to a large number of possible outcomes and thus leads to an extensive exploration of the search space. The use of Sobol sequence further enhances the exploration of the search space in terms of choosing the population members for mutation operation more evenly than the traditional approach. Therefore, it can be said that the CS-MOSADE algorithm acts as an effective tool for performing multi-objective design of WDNs.

### 4.4. Application of CS-MOSADE algorithm for WDN expansion

The CS-MOSADE algorithm is applied for WDN expansion and optimal pump scheduling for the three WDNs considering future changes in water demand for LCC minimization, reliability maximization and minimization of GHG emissions. The expansions are planned in terms of adding parallel pipes to the existing ones in stages of 10 years for a planning horizon of 50 years. Diurnal variation in water demand is considered to determine the optimal pump scheduling in terms of time intervals when the pump should be operated or closed. The pumping energy thus consumed is then used for estimation of GHG emissions. The Pareto optimal solutions obtained for three-objective optimization are presented in Fig. 6. The results of the 3-objective optimization are then plotted for only two objectives i.e., LCC and CERI, and compared to those obtained when GHG emissions are not considered in the model.

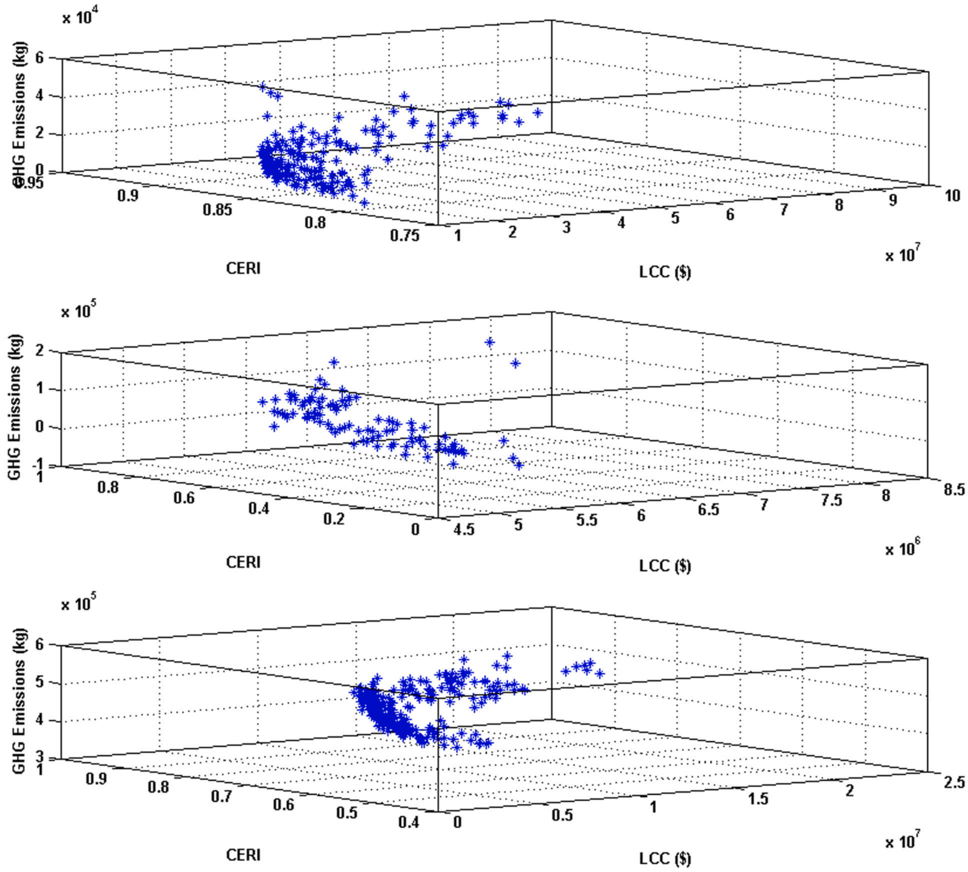


**Fig. 6.** Pareto-optimal front for WDN expansion for (a) Two loop (b) GoYang and (c) Al-Rahmaniya WDNs considering LCC minimization, reliability maximization and GHG emissions minimization.

The results are shown in Fig. 7. The two cases are categorised as scenario 1 (3-objective optimization) and scenario 2 (2-objective optimization) respectively. From Fig. 7(a), it can be seen that the least and highest cost solutions are different for the two cases. In case of scenario 1, the lowest and highest cost solutions are (12378533.61, 0.790) and (121403769.9, 0.943) respectively. While those for scenario 2 are (12066758.98, 0.792) and (129618905.6, 0.944) respectively. Thus, the optimal solution changes when GHG emissions are considered in the model. However, the GHG emission values are not correspondingly the lowest and highest in case of lowest and highest cost solutions. For example, the GHG emissions for the lowest and highest cost solutions for scenario 1 are 86327.38 kg and 98728.47 kg respectively. The GHG emission will be however, fixed value of 982430 kg, for scenario 2, assuming that the pumps will operate at all time periods. The solution corresponding to the lowest GHG emission is (58344331.31, 0.916). Similar observations can be made from Fig. 7(b) and Fig. 7(c) for GoYang and Al-Rahmaniya WDNs respectively. Thus, it can be seen that a trade-off exists between LCC and reliability. However, there is no direct trade-off that exists between LCC and GHG emissions or reliability and GHG emissions. If we consider 0.8 as the minimum reliability to be maintained, the corresponding optimal solutions are 12833634.41 and 12721581.26 respectively for the two scenarios, with GHG emissions of 93460.47 and 982430 kg. Similar observations can be made from Fig. 7(b) and Fig. 7 (c) for GoYang and Al-Rahmaniya WDNs respectively. Thus, it can be seen that a trade-off exists between LCC and reliability. However, there is no direct trade-off that exists between LCC and GHG emissions or reliability and GHG emissions.

A representative sample of solutions for the two benchmark WDNs for both the scenarios is presented in Table 4. The results are presented in terms of the diameter of parallel pipes to be added, the time at which these pipes need to be added, the head values at different nodes at the end of the planning horizon, and the pumping hours. In case of Two loop WDN, it can be seen that if we consider 0.8 as the minimum reliability to be maintained, the corresponding optimal solutions are 1.43 x $10^7$ and 1.36 x $10^7$ respectively for the two scenarios, with GHG emissions of 14103.6 and 26192.4 kg, with 19 and 24 h of pumping respectively. Thus, it can be seen that with a moderate increase in LCC, the emissions can be lowered by a considerable amount.

In case of Al-Rahmaniya WDN, a fixed GHG emission of 2.61 x $10^6$ kg requiring LCC of 1.88 x $10^7$ $ for reliability level of 0.81 occurs for scenario 2. However, the emission can be reduced to 0.44 x $10^6$ kg, for a reliability of 0.80 requiring an LCC of 2.43 x $10^7$ $ for scenario 1. This shows a huge reduction in GHG emissions of 2.17 x $10^6$ kg can be achieved at an additional cost of 0.55 x $10^7$ when optimal pump scheduling is incorporated in the model to minimize the GHG emissions. Thus, it can be seen that the LCC is although higher for scenario 1, the GHG emission is reduced. Therefore, the consideration of GHG emissions as a third objective leads to considerable benefits in terms of lower emissions, although requiring a slightly higher cost for the same reliability level.

## 5. Discussion

The comparison of the CS-MOSADE algorithm with past studies on the WDN design problems is presented in Table 5. The results are compared in terms of spacing metric, Number of function evaluations (NFE), generational distance, and different forms of hyper-volume (RHV, NHV, CNHV). The present study showed a better performance in terms of all these metrics. Lower spacing metric implies more evenly distributed Pareto optimal solutions, lower NFE implies lesser computational time needed, lower generational distance implies more convergence towards the true Pareto-optimal front. Higher value of HV again implies more converged Pareto-optimal front. Thus, it can be

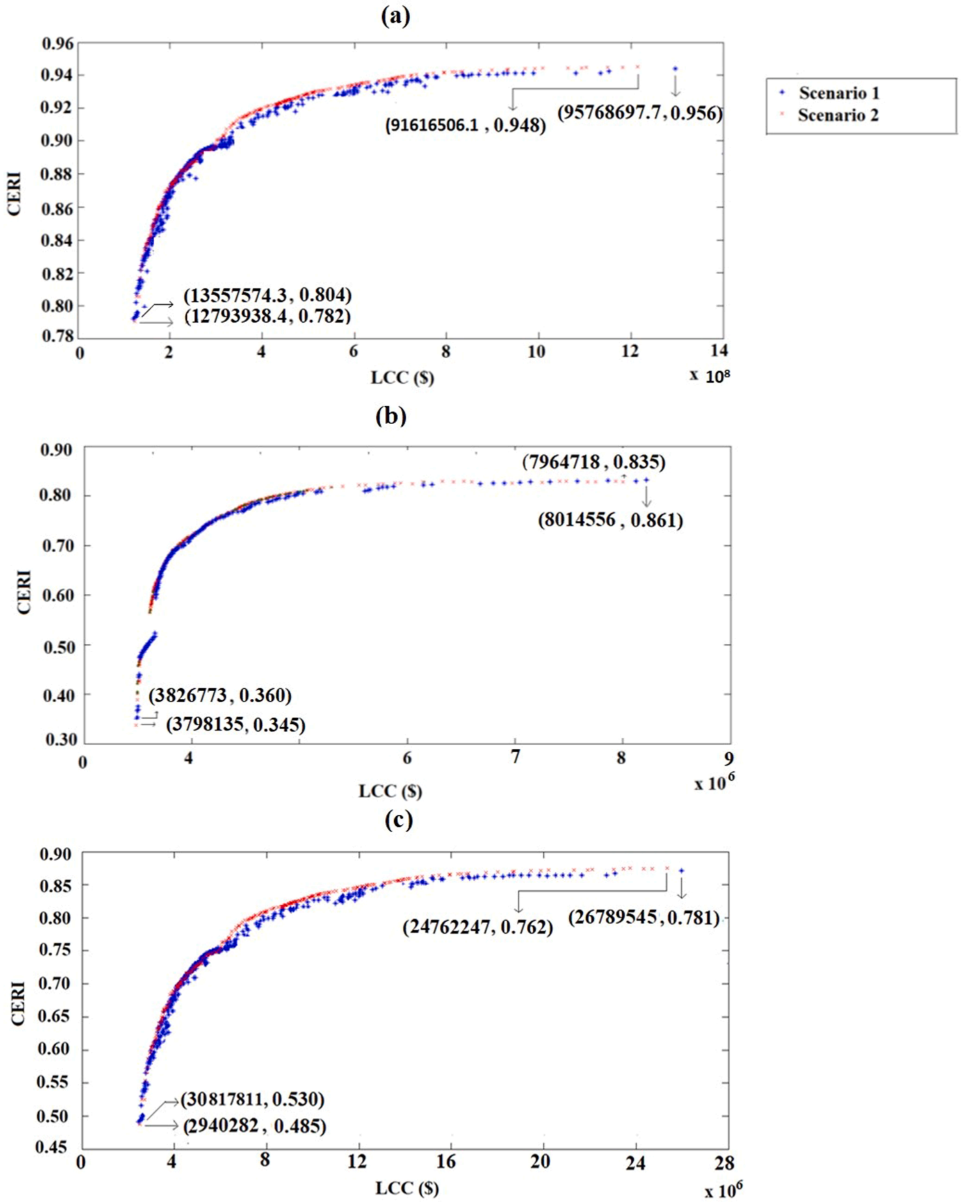


**Fig. 7.** Solutions of WDN expansion plotted to depict the trade-off between LCC and reliability for (a) Two loop (b) GoYang and (c) Al-Rahmaniya WDNs for two scenarios. Scenario 1: 3-objective optimization for minimizing LCC, maximizing reliability and minimizing GHG emissions, Scenario 2: 2-objective optimization for minimizing LCC and maximizing reliability.

**Table 4**
Comparison of a representative set of solutions obtained using CS-MOSADE for expansion of Two loop WDN.

| Scenario | Solution type | Solution (LCC ($), CERI, GHG emissions (kg)) | Diameter of parallel pipes (mm) | Time (in years) at which parallel pipes are to be added | Head values at nodes at the end of design period (m) | Total Pumping Hours |
|---|---|---|---|---|---|---|
| 1 | Solution with reliability 0.8 | (1.43 x $10^7$, 0.80, 14103.6 ) | (0, 304.8, 355.6, 152.4, 355.6, 254, 304.8,203.2, 0, 304.8, 406.4, 0, 355.6, 254, 304.8, 304.8) ) | (20, 20, 20, 20, 20, 30, 20 40, 20, 40, 30, 40, 50, 50, 40, 50) | (44.15, 65.10, 63.45, 64.94, 40.01, 39.10) | 19 |
| 2 | Solution with reliability 0.8 | (1.36 x $10^7$, 0.80, 26192.4 ) | (203.2, 304.8, 355.6, 254, 355.6, 203.2, 254, 254, 0, 355.6, 355.6, 0, 355.6, 203.2, 355.6, 254)) | (20, 20, 20, 30, 20, 20, 20, 40, 20, 40, 40, 50, 50, 50, 50, 50)) | (44.22, 61.98, 63.01, 66.32, 40.11, 39.35) | 24 |

concluded that the CS-MOSADE algorithm outperforms the algorithms applied in past studies in terms of lower computational time and better convergence to true Pareto-optimal fronts.

The present study tested and compared the performance of the hybrid CS-MOSADE for two benchmark WDNs composed of 8 and 30 pipes; and also applied it on a real network comprising of 339 pipes. Also, the present study considered future expansions by only modelling the changes in water demand, which sets certain limitations to the results of the analysis. This study, however, did not incorporate changes in water demand due to climatic and seasonal variations, these need to be

**Table 5**
Performance comparison of CS-MOSADE algorithm with past studies on WDN problems.

| WDN problem | Past study | Algorithm used (in past study) | Objectives used | Performance metric | Metric value Present study | Past study |
|---|---|---|---|---|---|---|
| Two loop | Choi et al. (2017) | SAMOHS[a] | Cost and resilience | Spacing metric | 0.0119 | 0.0187 |
| Two loop | Choi et al. (2017) | SAMOHS[a] | Cost and resilience | NFE[d] | 55000 | 60000 |
| Two loop | Choi et al. (2017) | SAMOHS[a] | Cost and resilience | Generational distance | $3.99 \times 10^{-05}$ | $2.10 \times 10^{-5}$ |
| Two loop | Sun et al. (2022) | MO-ASMOCH[b] | Cost and network resilience | Generational distance | $8.88 \times 10^{-3}$ | $8.54 \times 10^{-3}$ |
| Two loop | Sun et al. (2022) | MO-ASMOCH[b] | Cost and network resilience | RHV[e] | 0.994 | 0.938 |
| GoYang | Asadzadeh & Tolson (2011) | PA-DDS[c] | Cost and highest-pressure deficit | NHV[f] | 0.96 | 0.93 |
| GoYang | Asadzadeh & Tolson (2011) | PA-DDS[c] | Cost and highest-pressure deficit | CNHV[g] | 1.0 | 1.0 |

[a] : Self-Adaptive multi-objective harmony search,
[b] : multi-objective adaptive surrogate modelling-based optimization for constrained hybrid problems,
[c] : Hybrid Pareto archived dynamically dimensioned search,
[d] : Number of function evaluations,
[e] : Reduced hyper-volume,
[f] : Normalised hyper-volume,
[g] : Comparative Normalised hyper-volume

carefully considered before certain generalization can be made regarding optimal network design or operation.

## 6. Conclusions

This study presented and evaluated the CS-MOSADE algorithm for multi-objective design and expansion of WDNs. The CS-MOSADE algorithm was first applied and tested on three WDN problems for minimizing cost and maximizing reliability. The results were compared to those acquired through MOSADE and NSGA-II algorithms. Thereafter, the CS-MOSADE algorithm was applied for WDN expansion and optimal pump scheduling considering LCC minimization, reliability maximization and minimization of GHG emissions. The major conclusions that can be drawn based on the results obtained are as follows:

1. The CS-MOSADE algorithm is observed to converge two times and three times quicker than the MOSADE and NSGA-II algorithms, respectively. The CS-MOSADE algorithm also leads to better Pareto fronts in terms of larger percentage of solutions dominating the solutions obtained using other algorithms, more even Pareto fronts and better convergence towards the absolute Pareto optimal front. Thus, the CS-MOSADE algorithm is found to be an effective and reliable tool for solving the WDN design problem.
2. Consideration of GHG emissions in the optimization model leads to higher cost solutions for the same reliability level, but with lower emissions. This implies that GHG emissions can be lowered by consideration of optimal pump scheduling, but with higher expenditure. Therefore, optimal pump scheduling leads to some significant benefits in terms of low emissions and should be considered in optimal planning and operation of WDNs, which ultimately will lead to sustainable design and expansion solutions.

Future studies should, however, focus on consideration of other aspects that may affect the future changes in water demand, such as climatic and seasonal variations, land use/land cover change, change in water availability etc. Also, incorporation of other components such optimal allocation of tanks should be incorporated to study, if it leads to significant improvements in terms of reduction of cost and GHG emissions for reliability-based design and expansion problems.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The authors declare the following financial interests/personal relationships which may be considered as potential competing interests

### Data availability

Data will be made available on request.

### Acknowledgments

This research was supported by the American University of Sharjah, grant number FRG20-LE112. The authors would like to thank the colleagues at Sharjah Electricity, Water and Gas Authority; particularly from the Department of Research and Studies for their continuous support throughout the project.

### References

Alperovits, E., & Shamir, U. (1977). Design of optimal water distribution systems. *Water Resources Research, 13*, 885–900. https://doi.org/10.1029/WR013i006p00885
Alzaabi, M. S. A., & Mezher, T. (2021). Analyzing existing UAE national water, energy and food nexus related strategies. *Renewable and Sustainable Energy Reviews, 144*, Article 111031.
Artina, S., Bragalli, C., Erbacci, G., Marchi, A., & Rivi, M. (2011). Contribution of parallel NSGA-II in optimal design of water distribution networks. *Journal of Hydroinformatics, 14*, 310–323. https://doi.org/10.2166/hydro.2011.014
Asadzadeh, M., & Tolson, B. (2011). Hybrid Pareto archived dynamically dimensioned search for multi-objective combinatorial optimization: Application to water distribution network design. *Journal of Hydroinformatics, 14*, 192–205. https://doi.org/10.2166/hydro.2011.098
Awumah, K., Goulter, I., & Bhatt, S. K. (1990). Assessment of reliability in water distribution networks using entropy based measures. *Stochastic Hydrology and Hydraulics, 4*, 309–320. https://doi.org/10.1007/BF01544084
Babayan, A., Kapelan, Z., Savic, D., & Walters, G. (2005). Least-cost design of water distribution networks under demand uncertainty. *Journal of Water Resources Planning and Management, 131*, 375–382. https://doi.org/10.1061/(ASCE)0733-9496(2005)131:5(375)
Bao, Y., & Mays, L. W. (1990). Model for water distribution system reliability. *Journal of Hydraulic Engineering, 116*, 1119–1137. https://doi.org/10.1061/(ASCE)0733-9429(1990)116:9(1119)
Basupi, I., & Kapelan, Z. (2015). Flexible water distribution system design under future demand uncertainty. *Journal of Water Resources Planning and Management, 141*, Article 04014067. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000416
Bragalli, C., D'Ambrosio, C., Lee, J., Lodi, A., & Toth, P. (2012). On the optimal design of water distribution networks: A practical MINLP approach. *Optimization and Engineering, 13*, 219–246. https://doi.org/10.1007/s11081-011-9141-7
Branisavljević, N., Prodanović, D., & Ivetić, M. (2009). Uncertainty reduction in water distribution network modelling using system inflow data. *Urban Water Journal, 6*, 69–79. https://doi.org/10.1080/15730620802600916
Brest, J., Bošković, B., Greiner, S., Žumer, V., & Maučec, M. S. (2007). Performance comparison of self-adaptive and adaptive differential evolution algorithms. *Soft Computing, 11*, 617–629. https://doi.org/10.1007/s00500-006-0124-0
Brest, J., Greiner, S., Boskovic, B., Mernik, M., & Zumer, V. (2006). Self-adapting control parameters in differential evolution: A comparative study on numerical benchmark problems. *IEEE Transactions on Evolutionary Computation, 10*, 646–657. https://doi.org/10.1109/TEVC.2006.872133
Chi, H., Beerli, P., Evans, D. W., Mascagni, M., Sunderam, V. S., van Albada, G. D., Sloot, P. M. A., & Dongarra, J. (2005). On the Scrambled Sobol Sequence (Eds.). *Computational science – ICCS 2005* (pp. 775–782). Berlin, Heidelberg: Springer. https://doi.org/10.1007/11428862_105. Lecture notes in computer Science.

Choi, Y. H., Lee, H. M., Yoo, D. G., & Kim, J. H. (2017). Self-adaptive multi-objective harmony search for optimal design of water distribution networks. *Engineering Optimization, 49*, 1957–1977. https://doi.org/10.1080/0305215X.2016.1273910

Creaco, E., Franchini, M., & Walski, T. M. (2014b). Accounting for phasing of construction within the design of water distribution networks. *Journal of Water Resources Planning and Management, 140*, 598–606. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000358

Creaco, E., Franchini, M., & Todini, E. (2016). The combined use of resilience and loop diameter uniformity as a good indirect measure of network reliability. *Urban Water Journal, 13*(2), 167–181.

Cunha, M., & Marques, J. (2020). A new multiobjective simulated annealing algorithm – MOSA-GR: Application to the optimal design of water distribution networks. *Water Resources Research, 56*. https://doi.org/10.1029/2019WR025852. e2019WR025852.

Datta, R., & Regis, R. G. (2016). A surrogate-assisted evolution strategy for constrained multi-objective optimization. *Expert Systems with Applications, 57*, 270–284. https://doi.org/10.1016/j.eswa.2016.03.044

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation, 6*, 182–197. https://doi.org/10.1109/4235.996017

El Ansary, A. M., & Shalaby, M. F. (2014). Evolutionary optimization technique for site layout planning. *Sustainable Cities and Society, 11*, 48–55. https://doi.org/10.1016/j.scs.2013.11.008

Ezzeldin, R., Djebedjian, B., & Saafan, T. (2014). Integer discrete particle swarm optimization of water distribution networks. *Journal of Pipeline Systems Engineering and Practice, 5*, Article 04013013. https://doi.org/10.1061/(ASCE)PS.1949-1204.0000154

Ezzeldin, R. M., & Djebedjian, B. (2020). Optimal design of water distribution networks using whale optimization algorithm. *Urban Water Journal, 17*, 14–22. https://doi.org/10.1080/1573062X.2020.1734635

Fang, G., Guo, Y., Wen, X., Fu, X., Lei, X., Tian, Y., & Wang, T. (2018). Multi-objective differential evolution-chaos shuffled frog leaping algorithm for water resources system optimization. *Water Resources Management, 32*, 3835–3852. https://doi.org/10.1007/s11269-018-2021-6

Fujiwara, O., Jenchaimahakoon, B., & Edirishinghe, N. C. P. (1987). A modified linear programming gradient method for optimal design of looped water distribution networks. *Water Resources Research, 23*, 977–982. https://doi.org/10.1029/WR023i006p00977

Geem, Z. W. (2006). Optimal cost design of water distribution networks using harmony search. *Engineering Optimization, 38*, 259–277. https://doi.org/10.1080/03052150500467430

Geranmehr, M., Asghari, K., & Chamani, M. R. (2019). Uncertainty analysis of water distribution networks using type-2 fuzzy sets and parallel genetic algorithm. *Urban Water Journal, 16*, 193–204. https://doi.org/10.1080/1573062X.2019.1648527

Gharooni-fard, G., Moein-darbari, F., Deldari, H., & Morvaridi, A. (2010). Scheduling of scientific workflows using a chaos-genetic algorithm. *Procedia Computer Science, 1*, 1445–1454. https://doi.org/10.1016/j.procs.2010.04.160. ICCS 2010.

Jayaram, N., & Srinivasan, K. (2008). Performance-based optimal design and rehabilitation of water distribution networks using life cycle costing. *Water Resources Research, 44*. https://doi.org/10.1029/2006WR005316

Ji, L., Liang, S., Qu, S., Zhang, Y., Xu, M., Jia, X., Jia, Y., Niu, D., Yuan, J., Hou, Y., Wang, H., Chiu, A. S. F., & Hu, X. (2016). Greenhouse gas emission factors of purchased electricity from interconnected grids. *Applied Energy, 184*, 751–758. https://doi.org/10.1016/j.apenergy.2015.10.065

Johns, M. B., Keedwell, E., & Savic, D. (2019). Knowledge-based multi-objective genetic algorithms for the design of water distribution networks. *Journal of Hydroinformatics, 22*, 402–422. https://doi.org/10.2166/hydro.2019.106

Keedwell, E., & Khu, S. T. (2005). A hybrid genetic algorithm for the design of water distribution networks. *Engineering Applications of Artificial Intelligence, 18*, 461–472. https://doi.org/10.1016/j.engappai.2004.10.001

Keedwell, E., & Khu, S. T. (2006). A novel evolutionary meta-heuristic for the multi-objective optimization of real-world water distribution networks. *Engineering Optimization, 38*(03), 319–333.

Lee, S., Yoo, D. G., Jung, D., & Kim, J. H. (2018). Application of life cycle energy analysis for designing a water distribution network. *International Journal of Life Cycle Assessment, 23*, 1174–1191. https://doi.org/10.1007/s11367-017-1346-3

Li, F., Song, L., Cong, B., Hassanien, A. E., Bhatnagar, R., & Darwish, A. (2021). Reactive power optimization approach based on chaotic particle swarm optimization (Eds.). *Advanced machine learning technologies and applications, advances in intelligent systems and computing* (pp. 131–137). Singapore: Springer. https://doi.org/10.1007/978-981-15-3383-9_12.

Liu, J., & Lampinen, J. (2005). A fuzzy adaptive differential evolution algorithm. *Soft Computing, 9*, 448–462. https://doi.org/10.1007/s00500-004-0363-x

Liu, W., Song, Z., & Ouyang, M. (2020). Lifecycle operational resilience assessment of urban water distribution networks. *Reliability Engineering & System Safety, 198*, Article 106859. https://doi.org/10.1016/j.ress.2020.106859

Loganathan, G. V., Park, S., & Sherali, H. D. (2002). Threshold break rate for pipeline replacement in water distribution systems. *Journal of Water Resources Planning and Management, 128*, 271–279. https://doi.org/10.1061/(ASCE)0733-9496(2002)128:4(271)

Maier, H. R., Simpson, A. R., Zecchin, A. C., Foong, W. K., Phang, K. Y., Seah, H. Y., & Tan, C. L. (2003). Ant colony optimization for design of water distribution systems. *Journal of Water Resources Planning and Management, 129*, 200–209. https://doi.org/10.1061/(ASCE)0733-9496(2003)129:3(200)

Manolis, A., Sidiropoulos, E., & Evangelides, C. (2021). Targeted path search algorithm for optimization of water distribution networks. *Urban Water Journal, 18*, 195–207. https://doi.org/10.1080/1573062X.2021.1877739

Mansouri, R., Torabi, H., Hoseini, M., & Morshedzadeh, H. (2015). Optimization of the water distribution networks with differential evolution (DE) and mixed integer linear programming (MILP). *Journal of Water Resource and Protection, 7*, 715–729. https://doi.org/10.4236/jwarp.2015.79059

Marques, J., Cunha, M., & Savić, D. (2018). Many-objective optimization model for the flexible design of water distribution networks. *Journal of Environmental Management, 226*, 308–319. https://doi.org/10.1016/j.jenvman.2018.08.054

Mehzad, N., Asghari, K., & Chamani, M. R. (2020). Application of clustered-NA-ACO in three-objective optimization of water distribution networks. *Urban Water Journal, 17*, 1–13. https://doi.org/10.1080/1573062X.2020.1734633

Moazeni, F., & Khazaei, J. (2021). Interactive nonlinear multiobjective optimal design of water distribution systems using Pareto navigator technique. *Sustainable Cities and Society, 73*, Article 103110. https://doi.org/10.1016/j.scs.2021.103110

Monsef, H., Naghashzadegan, M., Jamali, A., & Farmani, R. (2019). Comparison of evolutionary multi objective optimization algorithms in optimum design of water distribution network. *Ain Shams Engineering Journal, 10*(1), 103–111.

Montalvo, I., Izquierdo, J., Schwarze, S., & Pérez-García, R. (2010). Multi-objective particle swarm optimization applied to water distribution systems design: An approach with human interaction. *Mathematical and Computer Modelling, 52*, 1219–1227. https://doi.org/10.1016/j.mcm.2010.02.017. Mathematical Models in Medicine, Business & Engineering 2009.

Muhuri, P. K., & Nath, R. (2019). A novel evolutionary algorithmic solution approach for bilevel reliability-redundancy allocation problem. *Reliability Engineering & System Safety, 191*, Article 106531. https://doi.org/10.1016/j.ress.2019.106531

Nandi, S., & Janga Reddy, M. (2020). Comparative performance evaluation of self-adaptive differential evolution with GA, SCE and DE algorithms for the automatic calibration of a computationally intensive distributed hydrological model. *H2Open Journal, 3*, 306–327. https://doi.org/10.2166/h2oj.2020.030

Özer, G., Ertokatlı, C.T., 2010. Chaotic processes of common stock index returns: An empirical examination on Istanbul stock exchange (ISE) market (SSRN Scholarly Paper No. 1617929). Social Science Research Network, Rochester, NY. 10.2139/ssrn.1617929.

Pant, M., Thangaraj, R., Singh, V. P., & Abraham, A. (2008). Particle swarm optimization using Sobol mutation. In *Proceedings of the 1st international conference on emerging trends in engineering and technology* (pp. 367–372). https://doi.org/10.1109/ICETET.2008.35. Presented at the 2008 first international conference on emerging trends in engineering and technology.

Peng, C., Liu, H. L., & Gu, F. (2017). An evolutionary algorithm with directed weights for constrained multi-objective optimization. *Applied Soft Computinging, 60*, 613–622. https://doi.org/10.1016/j.asoc.2017.06.053

Piratla, K. R., Ariaratnam, S. T., & Cohen, A. (2012). Estimation of $CO_2$ emissions from the life cycle of a potable water pipeline project. *Journal of Management in Engineering, 28*, 22–30. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000069

Prasad, T. D., & Park, N.-S. (2004). Multiobjective genetic algorithms for design of water distribution networks. *Journal of Water Resources Planning and Management, 130*, 73–82. https://doi.org/10.1061/(ASCE)0733-9496(2004)130:1(73)

Qin, A. K., & Suganthan, P. N. (2005). Self-adaptive differential evolution algorithm for numerical optimization. In *, 2. Proceedings of the IEEE congress on evolutionary computation* (pp. 1785–1791). https://doi.org/10.1109/CEC.2005.1554904. Presented at the 2005 IEEE congress on evolutionary computation.

Raad, D. N., Sinske, A. N., & van Vuuren, J. H. (2010). Comparison of four reliability surrogate measures for water distribution systems design. *Water Resources Research, 46*. https://doi.org/10.1029/2009WR007785

Samani, H. M. V., & Mottaghi, A. (2006). Optimization of water distribution networks using integer linear programming. *Journal of Hydraulic Engineering, 132*, 501–509. https://doi.org/10.1061/(ASCE)0733-9429(2006)132:5(501)

Savic, D. A., & Walters, G. A. (1997). Genetic algorithms for least-cost design of water distribution networks. *Journal of Water Resources Planning and Management, 123*, 67–77. https://doi.org/10.1061/(ASCE)0733-9496(1997)123:2(67)

Schott, J. R., & Jason, R. (1995). *Fault tolerant design using single and multicriteria genetic algorithm optimization*. Massachusetts Institute of Technology (Thesis).

Shamir, U., & Howard, C. D. D. (1981). Water supply reliability theory. *Journal AWWA, 73*, 379–384. https://doi.org/10.1002/j.1551-8833.1981.tb04736.x

Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal, 27*, 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Shibu, A., & Reddy, M. J. (2014). Optimal design of water distribution networks considering fuzzy randomness of demands using cross entropy optimization. *Water Resources Management, 28*, 4075–4094. https://doi.org/10.1007/s11269-014-0728-6

Sirsant, S., & Janga Reddy, M. (2018). Reliability-based design of water distribution networks using self-adaptive differential evolution algorithm. *ISH Journal of Hydraulic Engineering, 24*, 198–212. https://doi.org/10.1080/09715010.2017.1408038

Sirsant, S., & Reddy, M. J. (2021). Optimal design of pipe networks accounting for future demands and phased expansion using integrated dynamic programming and differential evolution approach. *Water Resources Management, 35*, 1231–1250. https://doi.org/10.1007/s11269-021-02777-8

Sirsant, S., & Reddy, M. J. (2020). Assessing the performance of surrogate measures for water distribution network reliability. *Journal of Water Resources Planning and Management, 146*, Article 04020048. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001244

Su, Y. C., Mays, L. W., Duan, N., & Lansey, K. E. (1987). Reliability-based optimization model for water distribution systems. Am. Soc. Civ. Eng. *Journal of the Hydraulics Division, 113*, 1539–1556. https://doi.org/10.1061/(ASCE)0733-9429(1987)113:12(1539)

Sun, R., Duan, Q., & Mao, X. (2022). A multi-objective adaptive surrogate modelling-based optimization algorithm for constrained hybrid problems. *Environmental Modelling & Software, 148*, Article 105272. https://doi.org/10.1016/j.envsoft.2021.105272

Suribabu, C. R. (2012). Heuristic-based pipe dimensioning model for water distribution networks. *Journal of Pipeline Systems Engineering and Practice, 3*, 115–124. https://doi.org/10.1061/(ASCE)PS.1949-1204.0000104

Suribabu, C. R. (2009). Differential evolution algorithm for optimal design of water distribution networks. *Journal of Hydroinformatics, 12*, 66–82. https://doi.org/10.2166/hydro.2010.014

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

Tanyimboh, T. T. (2017). Informational entropy: A failure tolerance and reliability surrogate for water distribution networks. *Water Resources Management, 31*, 3189–3204. https://doi.org/10.1007/s11269-017-1684-8

Tanyimboh, T. T., & Templeman, A. B. (1993). Maximum entropy flows for single-source networks. *Engineering Optimization, 22*, 49–63. https://doi.org/10.1080/03052159308941325

Teo, J. (2006). Exploring dynamic self-adaptive populations in differential evolution. *Soft Computing, 10*, 673–686. https://doi.org/10.1007/s00500-005-0537-1

Todini, E. (2000). Looped water distribution networks design using a resilience index based heuristic approach. *Urban Water, 2*, 115–122. https://doi.org/10.1016/S1462-0758(00)00049-2. Developments in water distribution systems.

Tolson, B. A., Maier, H. R., Simpson, A. R., & Lence, B. J. (2004). Genetic algorithms for reliability-based optimization of water distribution systems. *Journal of Water Resources Planning and Management, 130*, 63–72. https://doi.org/10.1061/(ASCE)0733-9496(2004)130:1(63)

Torkomany, M. R., Hassan, H. S., Shoukry, A., Abdelrazek, A. M., & Elkholy, M. (2021). An Enhanced multi-objective particle swarm optimization in water distribution systems design. *Water, 13*, 1334. https://doi.org/10.3390/w13101334

Tsegaye, S., Gallagher, K. C., & Missimer, T. M. (2020). Coping with future change: Optimal design of flexible water distribution systems. *Sustainable Cities and Society, 61*, Article 102306. https://doi.org/10.1016/j.scs.2020.102306

Valis, D., Vintr, Z., Hasilova, K., & Forbelska, M. (2022). Reliability assessment of water distribution network using specific forms of state space models. *Urban Water Journal, 19*, 109–118. https://doi.org/10.1080/1573062X.2021.1959622

Vamvakeridou-Lyroudia, L. S., Walters, G. A., & Savic, D. A. (2005). Fuzzy multiobjective optimization of water distribution networks. *Journal of Water Resources Planning and Management, 131*, 467–476. https://doi.org/10.1061/(ASCE)0733-9496(2005)131:6(467)

van Laarhoven, K., Vertommen, I., & van Thienen, P. (2018). Technical note: Problem-specific variators in a genetic algorithm for the optimization of drinking water networks. *Drinking Water Engineering and Science, 11*, 101–105. https://doi.org/10.5194/dwes-11-101-2018

van Veldhuizen, D. A., & Lamont, G. B. (1999). Multiobjective evolutionary algorithm test suites. In *Proceedings of the ACM symposium on applied computing, SAC '99* (pp. 351–357). https://doi.org/10.1145/298151.298382. Association for Computing Machinery.

Vasan, A., & Simonovic, S. P. (2010). Optimization of water distribution network design using differential evolution. *Journal of Water Resources Planning and Management, 136*, 279–287. https://doi.org/10.1061/(ASCE)0733-9496(2010)136:2(279)

Wagner, J. M., Shamir, U., & Marks, D. H. (1988). Water distribution reliability: Simulation methods. *Journal of Water Resources Planning and Management, 114*, 276–294. https://doi.org/10.1061/(ASCE)0733-9496(1988)114:3(276)

Wannakarn, P., Khamsawang, S., Pothiya, S., & Jiriwibhakorn, S. (2010). Optimal power flow problem solved by using distributed Sobol particle swarm optimization. In *Proceedings of the ECTI-CON2010: The ECTI international conference on electrical engineering/electronics, computer, telecommunications and information technology* (pp. 445–449). Presented at the ECTI-CON2010: The 2010 ECTI international confernce on electrical engineering/electronics, computer, telecommunications and information technology.

Weisser, D. (2007). A guide to life-cycle greenhouse gas (GHG) emissions from electric supply technologies. *Energy, 32*(9), 1543–1559.

Wu, G., Li, M., & Li, Z. S. (2021). A gene importance based evolutionary algorithm (GIEA) for identifying critical nodes in cyber–physical power systems. *Reliability Engineering & System Safety, 214*, Article 107760. https://doi.org/10.1016/j.ress.2021.107760

Wu, W., Maier, H. R., & Simpson, A. R. (2013). Multiobjective optimization of water distribution systems accounting for economic cost, hydraulic reliability, and greenhouse gas emissions. *Water Resources Research, 49*, 1211–1225. https://doi.org/10.1002/wrcr.20120

Wu, W., Simpson, A. R., & Maier, H. R. (2010). Accounting for greenhouse gas emissions in multiobjective genetic algorithm optimization of water distribution systems. *Journal of Water Resources Planning and Management, 136*, 146–155. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000020

Xie, Q., Wang, J., Lu, S., & Hensen, J. L. M. (2016). An optimization method for the distance between exits of buildings considering uncertainties based on arbitrary polynomial chaos expansion. *Reliability Engineering & System Safety, 154*, 188–196. https://doi.org/10.1016/j.ress.2016.04.018

Xu, C., & Goulter, I. C. (1998). Probabilistic model for water distribution reliability. *Journal of Water Resources Planning and Management, 124*, 218–228. https://doi.org/10.1061/(ASCE)0733-9496(1998)124:4(218)

Yang, Q., Beecham, S., Liu, J., & Pezzaniti, D. (2019). The influence of rainfall intensity and duration on sediment pathways and subsequent clogging in permeable pavements. *Journal of Environmental Management, 246*, 730–736. https://doi.org/10.1016/j.jenvman.2019.05.151

Yang, X., Yang, Z., Yin, X., & Li, J. (2008). Chaos gray-coded genetic algorithm and its application for pollution source identifications in convection–diffusion equation. *Communications in Nonlinear Science and Numerical Simulation, 13*, 1676–1688. https://doi.org/10.1016/j.cnsns.2007.03.003, 10.1016/j.scs.2021.103036.

Zecchin, A. C., Maier, H. R., Simpson, A. R., Leonard, M., & Nixon, J. B. (2007). Ant colony optimization applied to water distribution system design: Comparative study of five algorithms. *Journal of Water Resources Planning and Management, 133*, 87–92. https://doi.org/10.1061/(ASCE)0733-9496(2007)133:1(87)

Zhang, Q., Smith, K., Zhao, X., Jin, X., Wang, S., Shen, J., & Ren, Z. J. (2021). Greenhouse gas emissions associated with urban water infrastructure: What we have learnt from China's practice. *WIREs Water, 8*, e1529. https://doi.org/10.1002/wat2.1529

Zheng, F., Zecchin, A. C., Maier, H. R., & Simpson, A. R. (2016). Comparison of the searching behavior of NSGA-II, SAMODE, and Borg MOEAs applied to water distribution system design problems. *Journal of Water Resources Planning and Management, 142*, Article 04016017. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000650

Zheng, F., Zecchin, A. C., & Simpson, A. R. (2013). Self-adaptive differential evolution algorithm applied to water distribution system optimization. *Journal of Computing in Civil Engineering, 27*, 148–158. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000208

Zitzler, E., Thiele, L., Eiben, A. E., Bäck, T., Schoenauer, M., & Schwefel, H. P. (1998). Multiobjective optimization using evolutionary algorithms – A comparative case study (Eds.). *Parallel problem solving from nature – PPSN V* (pp. 292–301). Berlin, Heidelberg: Springer. https://doi.org/10.1007/BFb0056872. Lecture notes in computer science.