Invited Review

Evolutionary algorithms, swarm intelligence methods, and their applications in water resources engineering: a state-of-the-art review

M. Janga Reddy and D. Nagesh Kumar

Abstract

During the last three decades, the water resources engineering field has received a tremendous increase in the development and use of meta-heuristic algorithms like evolutionary algorithms (EA) and swarm intelligence (SI) algorithms for solving various kinds of optimization problems. The efficient design and operation of water resource systems is a challenging task and requires solutions through optimization. Further, real-life water resource management problems may involve several complexities like nonconvex, nonlinear and discontinuous functions, discrete variables, a large number of equality and inequality constraints, and often associated with multi-modal solutions. The objective function is not known analytically, and the conventional methods may face difficulties in finding optimal solutions. The issues lead to the development of various types of heuristic and meta-heuristic algorithms, which proved to be flexible and potential tools for solving several complex water resources problems. This paper provides a review of state-of-the-art methods and their use in planning and management of hydrological and water resources systems. It includes a brief overview of EAs (genetic algorithms, differential evolution, evolutionary strategies, etc.) and SI algorithms (particle swarm optimization, ant colony optimization, etc.), and applications in the areas of water distribution networks, water supply, and wastewater systems, reservoir operation and irrigation systems, watershed management, parameter estimation of hydrological models, urban drainage and sewer networks, and groundwater systems monitoring network design and groundwater remediation. This paper also provides insights, challenges, and need for algorithmic improvements and opportunities for future applications in the water resources field, in the face of rising problem complexities and uncertainties.

Key words: evolutionary algorithms, optimization, swarm intelligence, water resources

Highlights

- This paper reviews working principles and applications of evolutionary algorithms.
- This paper reviews working principles and applications of swarm intelligence algorithms.
- Discusses the issues and merits of various meta-heuristic algorithms.
- Provides insights and future research directions.
INTRODUCTION

Over the last few decades, there has been rising concern about global warming and associated changes in rainfall, streamflows, and water availability in the river basins. Many regions are often facing a shortage of water, as they receive rainfall in a particular season only, but the water demands have to be satisfied for the entire year. There is an ever-increasing demand for water to meet the diverse needs of society majorly for domestic, industrial, and agricultural purposes. Also, the efficient use of limited water for different users imposes substantial difficulties with conflicting goals (Reddy & Kumar 2006). Therefore, planning, construction, development, and operational activities of water resources projects warrant for solutions using systematic procedures. They can help planners to develop improved designs and operational systems, decide innovative management policies, improve and calibrate simulation models, and resolve conflicts between conflicting stakeholders (Maier et al. 2014). The complexity of systems models in water resources engineering has increased tremendously, with several socio-environmental–ecological issues and requires better alternative methods. In general, systems aim to reduce the total system cost or failure risk, maximize net benefits by providing an efficient design or operation policy. One of the important engineering tools that can be used in such events is the optimization tool, which helps to find a set of values of the decision variables subject to the various constraints that will produce the desired optimum response for the chosen objective function. As computers have become more powerful, the size and complexity of problems that can be simulated and solved by optimization techniques have correspondingly expanded.

Today there are a variety of optimization techniques existing to tackle different issues in practical problems of water resources. Some techniques (like exact methods) may provide optimal solutions for smaller problems, and others like meta-heuristic techniques may provide near-optimal solutions while solving large-scale water resources problems. A taxonomy or classification of optimization methods is given in Figure 1. But no single optimization method or algorithm is unanimously declared as the winner that can be applied efficiently to all types of problems. The method chosen for any particular case will depend primarily on (Reddy & Kumar 2012): (1) complexity of the problem, and the character of the objective function whether it is known explicitly, (2) the number and nature of the constraints, equality and inequality constraints, (3) the number of continuous and discrete variables, etc.
The commonly used methods in water resources include linear programming (LP), dynamic programming (DP), and nonlinear programming (NLP) methods. The LP method can guarantee global-optimal solutions for linear problems and has wider applications in water resources, like for irrigation planning, reservoir operation, conjunctive use planning, crop water allocation, seawater intrusion, command area management, etc. (Yeh 1985). But many practical water resources applications may involve nonlinear functions in optimization modeling for solving the problems. So the popular LP method cannot work in the case of models with nonlinear functions. The DP method
Bellman (1957) is popularly used for solving sequential decision making or multi-state decision-making problems in water resources. It can handle any kind of functional relationships in the model and can provide optimal solutions based on chosen interval values for the state and decision variables. The main applications in water resources are water allocation, reservoir operation, capacity expansion of water infrastructural facilities, water conveyance/shortest route-finding problems, etc. (Yakowitz 1982). Being a complete enumeration technique, the DP faces computational difficulties while solving large-size problems due to an increase in the number of state variables and the corresponding discrete states, since in the DP method, a linear increase in the number of state variables causes an exponential increase in computational time requirement. So, when DP is applied to larger-size problems, it has the main hurdle of the ‘curse of dimensionality’. The gradient-based NLP methods can solve problems with smooth nonlinear objectives and constraints. However, in large and highly nonlinear models, these algorithms may fail to find feasible solutions or converge to local optimum depending upon the degree of nonlinearity and an initial guess (Reddy & Kumar 2012). Hence, these traditional optimization techniques do not ensure global optimum and also have other limitations like requirements of objective functions to be continuous functions and easily differentiable, continuous variables, etc. Lack of ability to obtain a global optimum in the case of traditional nonlinear-optimization techniques and intensity of computational requirements in the case of dynamic programming motivated the search for new approaches, which would conglomerate efficiency and ability to find the global optimum.

In the recent past, nontraditional search and optimization methods based on natural and biological evolution, also called bio-inspired techniques, such as EA and swarm intelligence (SI) algorithms have been receiving increased attention in view of their potential as global optimization techniques for solving complex problems in water resources engineering (Reddy & Kumar 2012). Since, the first applications of genetic algorithms in the water resources area (McKinney & Lin 1994; Ritzel et al. 1994) and their acceptance as optimizers have increased tremendously for several practical applications in the water resources planning and management (Maier et al. 2014). However, there is a lack of synthesis between common algorithm challenges, common problem behaviors, and needed improvements for different key applications in the field. This paper will help the researchers to comprehend the algorithms and their applications in the planning and management of water resource systems. In the following first, the basic principles of EA and then some of the major types of EA are discussed.

**EVOlUTIONARY ALGORITHMS**

The EAs are rapidly expanding in the area of artificial intelligence research. During the last two decades, there has been a growing interest in algorithms, which are based on the principle of natural evolution (i.e., the survival of the fittest) (Fogel et al. 1966). The EAs are the population-based random search techniques guided with some heuristics (also called as meta-heuristic techniques). The EAs consist of a population of individuals, each representing a search point in the space of feasible solutions and is exposed to a collective learning process which proceeds from generation to generation (Brownlee 2011). The population is randomly initialized and then subjected to the process of selection, recombination, and mutation through several generations, such that the newly created generations evolve towards more favorable regions of the search space. The progress in the search is achieved by evaluating the fitness of all individuals in the population, selecting the individuals with a better fitness value, and combining them to create new individuals with an increased likelihood of improved fitness. After some generations, the program converges, and the best individual represents the optimum (or near-optimum) solution. There exist several EAs, but the basic structure of any evolutionary algorithm is very much the same (Reddy & Kumar 2012). A sample structure is shown in Figure 2.
The key steps involved in EA include:

1. Seeding the population using random generation
2. Evaluate the fitness of each individual in the population
3. Repeat the evolution steps until stopping criterion satisfied:
   (a) Select the individuals for reproduction
   (b) Perform genetic operations to generate the offspring
   (c) Evaluate the individual fitness of the offspring
   (d) Replace the least fit individuals with new best fit individuals
4. Report the best solution of the fittest individual.

The two most important issues in the evolution process are population diversity and selective pressure. These factors are strongly related to each other, i.e., an increase in the selective pressure decreases the diversity of the population and vice versa. In other words, strong selective pressure ‘supports’ the premature convergence of the search and a weak selective pressure can make the search ineffective. Different evolutionary techniques use different scaling methods and different selection schemes (e.g., probabilistic or proportional selection, ranking, tournament) to strike a balance between these two issues. Furthermore, these algorithms can be easily combined with local search and other exact methods. In addition, it is often straightforward to incorporate domain knowledge in the evolutionary operators and in the seeding of the population. Moreover, EAs can handle problems with any combination of the challenges that may be encountered in real-world applications, such as local optima and multiple objectives. The popular EAs are such as genetic algorithm (GA), evolutionary strategies (ES), evolutionary programming (EP), differential evolution (DE), etc. Some studies also proposed hybrid systems by combining features of more than one EA, and they exhibited significant results in several water resources applications. In the following, a brief overview of popular EAs is given with an emphasis on showing how the various types of algorithms differ, and the stages involved in defining each one.

Figure 2 | The basic structure of an evolutionary algorithm (EA).
Genetic algorithms

GA is the most popular algorithm of EAs. GA was inspired by population genetics (like heredity and gene frequencies), and evolution at the population level besides the Mendelian understanding of the structure (like chromosomes, genes, alleles) and process/mechanisms (like recombination and mutation) (Fogel et al. 1966; Goldberg 1989). The basic GA was introduced by Holland (1975) based on the binary encoding of the solution parameters, utilizes multi-point crossover and bit-flip mutation for the evolution of the solutions. Later, several variants of GA (binary/real coding) with a variety of genetic operators were developed and used in various water resources applications. The working of GA involves random initialization of population (i.e., members are randomly generated to cover the entire search space uniformly) to start the process. Then, evaluation of the objective functions, selection of parents, and applying genetic operations, recombination operator for creation of offspring, and mutation operation for perturbing the individuals to produce a new population are conducted. The steps are repeated until a termination condition is satisfied. A sample pseudo-code of GA, describing the key steps in the algorithm, is depicted in Figure 3(a).

Recently, real-coded GA has been receiving more recognition and applications. There exist several variants of crossover operators (arithmetic, simulated binary crossover, Blend crossover, etc.) and

(a) Genetic algorithm

begin
2: define problem dimension (D), generate initial population $P_0$ of size $NP$
3: evaluate the fitness of $NP$ individuals in $P_0$
4: initialize generation counter $t ← 0$
5: while termination criterion not satisfied do
6:  selection of parents on the basis of their fitness
7:  create offspring for the new generation $P_{t+1}$ from the parents using
crossover operation
8:  perform mutation on new generation $P_{t+1}$
9:  evaluate the fitness of population $P_{t+1}$
10: $t ← t+1$
11: end
12: end

(b) DE algorithm

begin
2: define problem dimension, generate an initial population with a given size
3: calculate the fitness of the initial population.
4: initialize generation counter $g ← 0$
5: while termination criterion not satisfied do
6:  for each population in current generation do
7:   select three solutions at random.
8:   generate one offspring using the DE operators (mutation, crossover).
9:   if offspring is more fit than parent then
10:     the parent is replaced with offspring
11: end
12: $g ← g+1$
13: end

Figure 3 | The pseudo-codes of evolutionary algorithms: (a) genetic algorithm (GA) and (b) differential evolution (DE).
mutation operators (e.g., Gaussian, polynomial, random mutation, etc.). The basic selection operator for GAs was proportional (or roulette-wheel) selection, but because of its known drawbacks of premature convergence to locally optimal solutions, tournament selection and ranking selection are commonly used nowadays. For numerical optimization, a real-coded GA with Gaussian mutation, arithmetic crossover, and tournament selection is a common choice. Moreover, an operation called elitism is remarkably important for the performance of a GA. The usage of elitism is to leave a certain proportion of the best individuals in every generation untouched by the variation operators. This is to some extent, similar to evolution strategies, where a population of parents generates a new offspring by a mutation in each iteration. The population of the next generation is created by selection from the elite parents and newly created offspring. Nicklow et al. (2010) presented an overview of the GA method and its applications in water resources management. By utilizing the strengths of EAs, quick convergence, and yielding efficient solutions for single-objective optimization, researchers also developed multi-objective algorithms by integrating Pareto optimality principles into single-objective genetic algorithms, such as Nondominated Sorting Genetic Algorithms (NSGA-II; Deb et al. 2002), Multi-objective Evolutionary Algorithm (MOEA; Reddy & Kumar 2006), etc. Reed et al. (2013) discussed the principles of different MOEAs methods and their applications in water resources.

Different variants of GA were developed over the years, like Micro GA (Krishnakumar 1990), Cellular GA (Manderick & Speissens 1989), NSGA (Srinivas & Deb 1994), Contextual GA (Rocha 1995), Grouping GA (Falkenauer 1996), Quantum-inspired GA (Narayanan & Moore 1996), Linkage learning GA (Harik 1997), Island GA (Whitley et al. 1998), NSGA-II (Deb et al. 2002), Interactive GA (Takagi 2001), Jumping gene GA (Man et al. 2004), Dynamic rule-based GA (He & Hui 2006), Hierarchical cellular GA (Jonson et al. 2006), NSGAIII (Deb & Jain 2014), Tribe competition-based GA (Ma & Xia 2017), Fluid GA (Jafari-Marandi & Smith 2017), Block-based GA (Tseng et al. 2018), etc. Historical development of GA variants is also depicted in Figure 4. Although many of these variants use the same basic principles of natural selection and survival of the fittest, they engage different strategies and improved mechanisms in pursuit of better guidance of the search and aiding the enhanced convergence of the method. For example, for multi-objective optimization, the initial version of NSGA (proposed in 1994) was improved over the years and later proposed NSGA-II in 2002 and NSGAIII in 2014 by incorporating additional mechanisms (like nondominated sorting, crowding distance measures, etc.) to handle different issues and complexities of multi-objective optimization problems.

Differential evolution

Storn & Price (1996) proposed DE as a variant of EAs to achieve the goals of robustness in optimization and quick convergence to an optimal solution for numerical optimization. The DE contrasts from other EAs in the evolution process. Here mutation is the main operator, and the crossover is the secondary operator for the generation of new solutions (Reddy & Kumar 2012). After random initialization of the population, the objective functions are evaluated, and the following steps are repeated until a termination condition is satisfied. At each generation, two operators, namely mutation and crossover, are applied to each individual, to produce a new population. In DE, the mutation is the main operator, and each individual is updated using a weighted difference of a selected parent solution and crossover acts as background operator where the crossover is performed on each of the decision variables with a small probability. The offspring replaces the parent only if it improves the fitness value; otherwise, the parent is copied in the new population. The pseudo-code of the DE algorithm is given in Figure 3(b).

There are several variants of DE, depending on the number of weighted differences between solution vectors considered for perturbation, and the type of crossover operator (binary or
exponential) used (Storn & Price 1997). For example, in DE/rand-to-best/1/bin variant of DE: perturbation is made with the vector difference of best vector of the previous generation (best) and current solution vector, plus single vector differences of two randomly chosen vectors (rand) among the population. The DE variant uses the binomial (bin) variant of crossover operator, where the crossover is performed on each of the decision variables whenever a randomly picked number between 0 and 1 is within the crossover constant (CR) value. More details of DE can be found elsewhere (Price et al. 2005; Das et al. 2016). To generate Pareto-optimal solutions for multi-objective problems, researchers also developed different variants of multi-objective differential evolution algorithms (MODE; Reddy & Kumar 2007c).

Different variants of DE were developed over the years, like DE (Storn & Price 1997), Self-adaptive DE (SaDE; Qin & Suganthan 2005), jDE (Brest et al. 2006), Chaotic DE (Wang & Zhang 2007), adaptive DE with optional external archive (JADE; Zhang et al. 2009), ensemble of mutation strategies DE (EPSDE; Mallipeddi et al. 2011), Composite DE (CoDE; Wang et al. 2011b), Multi-population DE (Yu & Zhang 2011), Adaptive Cauchy DE (ACDE; Choi et al. 2013), improved JADE (Yang et al. 2014), Extended adaptive Cauchy DE (Choi & Ahn 2014), jDErpo (Brest et al. 2014), Restart DE algorithm with Local search mutation (RDEL; Ali 2014), Colonial competitive DE (Ghasemi et al. 2016), Memory-based DE (Parouha & Das 2016), Stochastic Quasi-Gradient (SQG)-DE (Sala et al. 2017), Unified DE (UDE; Trivedi et al. 2017), Opposition-based Compound Sinusoidal DE (OCSinDE; Draa et al. 2019), etc. The evolution of various DE variants is also depicted in Figure 4. The different variants of DE use different improved strategies and self-adaptive schemes for enhancing the convergence and consistency in solutions for single (or multiple) objective optimization problems. More details can be found in the referred papers.

---

**Figure 4** Evolution of different evolutionary algorithms and their variants developed over the years, showing for genetic algorithms (GA), differential evolution (DE), and evolution strategies (ES).
Evolutionary strategies

ES model evolution as a process of the adaptive behavior of the individual or in other words ES focus mutational transformations that maintain the behavioral linkage between each parent and its offspring, respectively, at the level of the individual (Rechenberg 1973; Fogel 1994). ES uses real variables and aims at numerical optimization. Because of that, the individuals incorporated could be a set of strategic parameters. ES rely mainly on the mutation operator (Gaussian noise with zero means). ES evolves by making a series of discrete adjustments (i.e., mutations) to an experimental structure. After each adjustment, the new structure, i.e., the offspring, is evaluated and compared to the previous structure, i.e., the parent. The better of the two is then chosen and used in the next cycle. As selection in this evolutionary cycle is made from one parent and one offspring, the algorithm is known as a ‘(1 + 1)’ ES.

These two-membered ES modify (i.e., mutate) an n-dimensional real-valued vector $x \in \mathbb{R}^n$ of object variables by adding a normally distributed random variable with expectation zero and standard deviation $\sigma$ to each of the object variables $x_i$. The standard deviation is the same for all components of $x$, i.e., $\forall i \in \{1, 2, \ldots, n\}: x'_i = x_i + \sigma N_i(0, 1)$, where $x'$ is the offspring of $x$ and $N_i(0; 1)$ is the realization of a normally distributed random variable with expectation 0 and standard deviation 1. Since the introduction of ES, two additional strategies have been developed: $(\mu + \lambda)$ and $(\mu, \lambda)$. Both of these ES work on populations rather than single individuals and are referred to as multi-membered ES. A $(\mu + \lambda)$ ES creates $\lambda$ off-springs from $\mu$ parents and selects the best $\mu$ individuals from the combined set of $\mu$ parents plus $\lambda$ off-springs to make the next population. A $(\mu, \lambda)$ ES, on the other hand, creates $\lambda$ off-springs and selects the best $\mu$ individuals from the off-springs alone (for $1 \leq \mu \leq \lambda$).

Different variants of ES were developed over the years, like Derandomized Self-adaptation ES (Ostermeier et al. 1994a), CSA-ES (Ostermeier et al. 1994b), CMA-ES (Hansen & Ostermeier 2001), Weighted multi-recombination ES (Arnold 2006), Meta-ES (Jung et al. 2007), Natural ES (Wierstra et al. 2008), Exponential natural ES (Glasmachers et al. 2010), Limited memory CMA-ES (Loshchilov 2014), Fitness inheritance CMA-ES (Liaw & Ting 2016), RS-CMSA ES (Ahrari et al. 2017), MA-ES (Beyer & Sendhoff 2017), Weighted ES (Akimoto et al. 2018), etc. The historical development of various ES variants is also depicted in Figure 4. The different variants use different strategies/adaptation schemes for better evolution and enhanced performance of the ES algorithm while solving a different kind of optimization problems. Apart from these, other EAs and their hybrid variants were proposed and used in solving water resources problems.

SWARM INTELLIGENCE

The other class of meta-heuristic techniques that are gaining more popularity in recent times for water resources optimization are SI techniques. The SI is based on the claims that intelligent human cognition derives from the interaction of individuals in a social environment. There exist several algorithms that use this socio-cognition, which can be used to solve different optimization tasks (Bonabeau et al. 1999). The individual members of a swarm act without supervision, and each of these members has a stochastic behavior due to their perception in the neighborhood. Swarms use their environment and resources effectively by collective group intelligence. The key characteristic of a swarm system is self-organization, which helps in evolving global level response by means of local-level interactions (Reddy 2009). The SI methods are also called behaviorally inspired algorithms.

The main algorithms that fall under SI algorithms include particle swarm optimization (PSO), artificial bee colony (ABC), ant colony optimization (ACO), honey-bee mating optimization (HBMO), firefly algorithms, etc. Similar to EAs, SI models are population-based iterative procedures. The system is randomly initialized with a population of individuals. These individuals are then manipulated and evolved over many iterations by way of mimicking the social behavior of insects or...
animals in an effort to find the optima. Unlike EAs, SI algorithms do not use evolutionary operators such as recombination and mutation. Basically, a potential solution flies through the search space by modifying itself according to its relationship with other individuals in the population and the environment (Reddy & Kumar 2012). The two algorithms that attracted the interest of many researchers and received wider applications in water resources are PSO and ACO for solving a variety of problems. PSO is based on the social behavior of fish schooling and bird flocking introduced by Eberhart & Kennedy (1995) and has received wider recognition for numerical optimization with continuous variables whereas ACO is basically inspired by the foraging search behavior of real ants and their ability to find shortest paths and was mainly used for discrete combinatorial optimization (Kennedy et al. 2001). In the following, a brief description of the basic principles and working of these two SI techniques is presented.

Particle swarm optimization

PSO algorithm proposed by Eberhart & Kennedy (1995) is a population-based meta-heuristic search technique that uses co-operative group intelligence concepts. Here the particle denotes individual in a swarm. Each particle in a swarm behaves in a distributed way using its own or cognitive intelligence and the collective or social (group) intelligence of the swarm. As such, if one particle discovers a good path to food, the rest of the swarm will also be able to follow the good path instantly even if their location is far away in the swarm. PSO shares many similarities with GA (Kumar & Reddy 2007). PSOs are initialized with a population of random solutions and searches for optima by updating iterations. However, in comparison to methods like GA, in PSO, no operators inspired by natural evolution are applied to extract a new generation of candidate solutions. Instead, PSO relies on the exchange of information between individuals (particles) of the population (swarm). In effect, each particle adjusts its trajectory towards its own previous best position and towards the best previous position attained by any other member of its neighborhood (usually the entire swarm) (Kennedy et al. 2001).

The PSO algorithm involves the following steps (Kumar & Reddy 2007): initialization of particles with a random position and velocity vectors. Then the fitness of each particle is evaluated by the fitness function. Two ‘best’ values are defined, the global and the personal bests. The global best is the highest fitness value in an entire iteration (best solution so far), and the personal best is the highest fitness value of a specific particle. Each particle is attracted to the location of the ‘best fitness achieved so far’ across the whole swarm. In order to achieve this, a particle stores the previously reached ‘best’ positions in a cognitive memory. The relative ‘pull’ of the global and the personal best is determined by the acceleration constants called social and cognitive parameters. After this update, each particle is then re-evaluated. If any fitness is greater than the global best, then the new position becomes the new global best. If the particle’s fitness value is greater than the personal best, then the current value becomes the new personal best. This procedure is repeated until the termination criteria are satisfied. The pseudo-code of the PSO algorithm is given in Figure 5(a). Further to speed up the convergence and to enhance the reliability in optimal solutions, different studies suggested additional mechanisms, like elitist mutation strategy (Reddy & Kumar 2007a), combining PSO with other local search methods and applied for different kinds of problems in water resources. By utilizing the strengths like faster convergence and efficient optimal solutions for single-objective optimization, researchers also developed multi-objective SI algorithms by integrating nondomination principles into single-objective PSO, for example, elitist-mutated multi-objective PSO (EM-MOPSO; Reddy & Kumar 2007b), etc.

There were several variants of PSO algorithms, and their hybrid algorithms developed over the years, like Constricted PSO (Shi & Eberhart 1998), Adaptive PSO (Clerc1999), Discrete PSO (Clerc 2004), Elitist-mutated PSO (EMPSO) (Reddy 2006), EM-MOPSO (Reddy 2006), Dynamic niching PSO (Nickabadi et al. 2008), Adaptive PSO (Zhan et al. 2009), Co-evolutionary MOPSO (Goh
et al. 2010), Self-adaptive learning PSO (Wang et al. 2011a), Multi-dimensional PSO (Kiranyaz et al. 2011), Hybrid niching PSO (NPSO; Li et al. 2012), Hybrid PSO-Harmony Search (PSO-HS; Li et al. 2012), Hybrid PSO-Firefly Algorithm (PSO-FFA; Bhushan & Pillai 2013), etc. The historical development of the PSO algorithm and its variants are depicted in Figure 6.

### Ant colony optimization

The first ACO algorithm was inspired by the foraging behavior exhibited (pheromone trail laying and training behavior) by ant colonies in their search for food (Dorigo et al. 1991). ACO was developed as a population-based, heuristic search technique for the solution of difficult combinatorial and complex problems. The main features of the ACO algorithm are pheromone trail and heuristic information (Kumar & Reddy 2006). The working of the ACO algorithm involves the following phases. First, the system is randomly initialized with a population of individuals. These individuals are then manipulated over many iterations by using some guiding principles in their search, such as a probability function based on the relative weighting of pheromone intensity and heuristic information),
in an effort to find the optima. At the end of each iteration, each of the ants adds pheromone to its path (set of selected options). The amount of pheromone added is proportional to the quality of the solution (for example, in the case of minimization problems, lower-cost solutions are better; hence they receive more pheromone). The pseudo-code of the ACO algorithm, depicting the key steps, is given in Figure 5(b).

An important characteristic of ACO one should be aware of is that it is a problem-dependent application. In order to adopt ACO for application to a particular problem, it requires representation of the problem as a graph or a similar structure easily covered by ants and assigning a heuristic preference to generated solutions at each time step. The ACO has many features, which are similar to that of GA (Dorigo & Stützle 2004; Kumar & Reddy 2006): (a) both are population-based stochastic search techniques; (b) GA works on the principle of survival of the fittest, whereas ACO works on pheromone trail laying behavior of ant colonies; (c) GA uses crossover and mutation as prime operators in its evolution for next generation, whereas ACO uses pheromone trail and heuristic information; (d) in ACO algorithms, trial solutions are constructed incrementally based on the information contained in the environment and the solutions are improved by modifying the environment through a form of indirect communication called stigmergy, whereas in GA, the trial solutions are in the form of strings of genetic materials and new solutions are obtained through modification of the previous solutions.

There were several variants of ACO algorithms and their hybrid algorithms developed over the years, like Ant System (AS; Dorigo et al. 1996), Ant Colony System (ACS; Dorigo & Gambardella 1997), Ant NET (Di Caro & Dorigo 1998), Max-Min AS (Stützle & Hoos 2000), Multiple ACS (Gambardella et al. 1999), Multi-Colony Ant Algorithms (Iredi et al. 2001), Population-based ACO for the dynamic environment (Guntsch & Middendorf 2002), ACO for WDNs (Maier et al. 2003), ACO for reservoir system (Reddy 2006), Beam-ACO (Blum 2008), hybrid genetic Simulated Annealing

**Figure 6** | Evolution of different swarm intelligence algorithms and their different variants developed over the years, showing for particle swarm optimization (PSO), ant colony optimization (ACO), and artificial bee colony (ABC) and other meta-heuristics.
(SA) ACS-PSO (Chen & Chien 2011), Hybrid ACO-PSO (Huang et al. 2013), Parallel ACO (Delé-Vacq et al. 2013), Hybrid PSO-fuzzy ACO (Elloumi et al. 2014), etc. The evolution of ACO and its variants are also portrayed in Figure 6.

Other swarm-based meta-heuristics

The other meta-heuristic algorithms that were proposed and applied in various fields for optimization include Harmony Search (HS; Geem et al. 2001), Shuffled Frog Leaping Algorithm (SFLA; Eusuff & Lansey 2003), Honey-Bee Mating Optimization (HBMO; Abbass 2001), Glowworm Swarm Optimization (GSO; Krishnanand & Ghose 2006), Firefly algorithm (FFA, Yang 2007), ABC (Karaboga 2005), Cuckoo Search (CS, Yang & Deb 2010), Bat Algorithm (Yang 2010), Multi-colony Bacteria Foraging Optimization (MC-BFO; Chen et al. 2010), etc. Table 1 gives brief details of these SI-based meta-heuristic algorithms and their working principles. The evolution of these meta-heuristics over the years and their hybrid variants are also shown in Figure 6.

**Table 1** | Swarm intelligence based meta-heuristic algorithms, development and their working principles

| Algorithm                                      | Proposed by year | Short description                                                                                                                                 |
|------------------------------------------------|------------------|-------------------------------------------------------------------------------------------------------------------------------------------------|
| Harmony Search (HS)                            | Geem et al. (2001) | Search works on the principle of a musician trying to identify a state of pleasing harmony and continuing to play the pitches to seek better harmony |
| Honey-Bee Mating Optimization (HBMO)           | Abbass (2001)     | The algorithm inspired by the mating process of bees                                                                                           |
| Shuffled Frog Leaping Algorithm (SFLA)         | Eusuff & Lansey (2003) | The social behavior of frogs inspired SFLA                                                                                                      |
| Artificial Bee Colony (ABC)                   | Karaboga (2005)   | The algorithm simulates the foraging process of the bees                                                                                         |
| Glowworm Swarm Optimization                    | Krishnanand & Ghose (2006) | The search imitates the behavior that a glowworm carries a luminescence quantity (called luciferin) along with itself to exchange information with cohorts |
| Firefly Algorithm (FFA)                        | Yang (2007)       | The algorithm inspired by the fireflies and their ability to emit light through the biochemical process (called bioluminescence)                |
| Bat Algorithm (BA)                             | Yang (2010)       | The algorithm inspired by the echolocation of bats                                                                                              |
| Cuckoo Search (CS)                             | Yang & Deb (2010)  | The algorithm is inspired by the obligate brood parasitism of some cuckoo species by laying their eggs in the nest of host birds                    |
| Multi-colony Bacteria Foraging Optimization (MC-BFO) | Chen et al. (2010) | The algorithm integrates the cell-to-cell communication strategies of multi-colony bacterial community with the chemotaxis (optimal foraging search capabilities) behavior of single cell |

The performance of meta-heuristic search methods is generally influenced by the parameter of the algorithm. Similar to EAs, these SI algorithms are also quite sensitive to set-up parameters (Reddy 2009). So it is important to fine-tune the parameters for a particular problem of interest before actually applying the same to the problem (Reddy & Kumar 2012).

**APPLICATIONS**

The EA and SI methods have emerged as a powerful tool for optimization and management of water resources problems. There are numerous applications of EAs for water-related problems, namely, reservoir operation, water distribution systems design, groundwater remediation, parameter estimation in hydrological modeling, watershed management, and fluvial systems, etc. Since there exist
several thousands of papers on applications of these algorithms, here, some of the important applications in water resources are reviewed.

Applications in water distribution systems

WDS comprises a system of interconnected nodes, via pipes, supply sources, such as reservoirs, tanks, and a set of hydraulic control elements, such as pumps, valves, regulators, etc. The network of interconnected nodes, pipes, and other hydraulic control elements is collectively termed as a water distribution network (WDN). A typical WDN design is formulated as an optimization problem requiring minimization of cost, satisfying the minimum pressure and flow requirements at different nodes. A variety of EA were applied for design and rehabilitation of WDNs, like GA (Simpson et al. 1994; Mackle et al. 1995; Savic & Walters 1997; Dandy & Engelhardt 2001; Munavalli & Kumar 2003; van Zyl et al. 2004; Keedwell & Khu 2005; Vairavamoorthy & Ali 2005; Wu & Walski 2005; Rao & Salomons 2007; Kadu et al. 2008); Ant Colony optimization (ACO; Maier et al. 2003), Differential Evolution (DE) (Suribabu 2010; Vasan & Simonovic 2010; Sirsant & Reddy 2018), SFLA (Eusuff & Lansey 2003); Harmony search (HS) algorithm (Geem 2006), Tabu search (TS) algorithm (Cunha & Ribeiro 2004), Honey-bee mating optimization (HBMO; Mohan & Babu 2010) Cross entropy (CE) optimization (Shibu & Reddy 2014); Gravitational search algorithm (GSA, Fallah et al. 2019), etc. More details of these applications are given in Table 2.

Further, there were several studies that have used multi-objective EA for multi-objective optimization of WDNs. In order to ensure satisfactory performance of WDNs at different failure conditions, the objectives such as reliability, minimum surplus head, etc., are incorporated into the model in addition to the minimization of cost of the network. The reliability expressed as the performance of the network in terms of demand satisfaction considering these failure conditions. Failures can be hydraulic or mechanical; here, hydraulic failure occurs due to uncertainty in input parameters like nodal demands, and pipe roughness coefficients, whereas mechanical failure occurs due to failure of one or more components such as pipes, pumps, valves, etc. (Sirsant & Reddy 2018). Different reliability indicators are employed in different studies as the objective function to be maximized along with minimization of cost. Different variants of GA techniques were used for the multi-objective design of WDNs such as Multi-objective GA (MOGA; Halhal et al. 1997; Savic et al. 1997; Vamvakkeridou-Lyroudia et al. 2005; Dandy & Engelhardt 2006); Strength Pareto Evolutionary Algorithm (SPEA; Cheung et al. 2003), Nondominated Sorting GA-II (NSGA-II; Prasad et al. 2004; Prasad & Park 2004; Farmani et al. 2005; Kapelan et al. 2005; Ostfeld & Salomons 2006; Jayaram & Srinivasan 2008; Prasad & Tanyimboh 2008; Creaco et al. 2014; Sirsant & Reddy 2020); Multi-objective PSO (Patil et al. 2020), etc. More details and discussion of these applications is given in Table 3.

Applications in urban drainage and sewer systems

Urban drainage and sewer systems need to be designed such that the required flow capacity is met at minimum cost. The consideration of networks where both stormwater and sewage are transported through the same channel makes the problem a little more complex. Various studies used different EAs for the design of urban drainage and sewer systems like GA (Walters & Lohbeck 1993; Walters & Smith 1995; Liang et al. 2004; Afshar et al. 2006; Guo et al. 2006) SA (Karovic & Mays 2014), TS (Liang et al. 2004), DE method (Yazdi 2018), etc. More details of these applications are explained in Table 4. In addition to carrying the required flow during normal conditions, the high and extreme flow conditions such as flooding overflows should be considered to make the system more robust to such situations. This calls for the need to perform the multi-objective design of these systems considering minimization of the flooding overflow volume or flood damage cost, in addition to the minimization of cost. Different MOEAs were engaged for solving these problems, such as NSGA-II (Barreto et al. 2010).
| Author(s) (year)   | Technique used | Work and objectives                                                                 | Case studies/problems considered          | Key findings                                                                                                                                                                                                 |
|-------------------|----------------|-------------------------------------------------------------------------------------|-------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Simpson et al. (1994) | GA             | Application of GA on WDN design problem considering maximization of the reciprocal of total network cost | WDN of Gessler (1985)                    | GA can provide an optimal and a set of sub-optimal solutions, while other techniques provide only a single solution. Also, complete enumeration and NLP methods can be applied only to small networks.               |
| Mackle et al. (1995)  | GA             | Application of GA for optimal pump scheduling for minimization of energy cost subject to reservoir filling and emptying constraints | Example WDN problem                      | The efficacy of GA proved for solving pump scheduling problems and noted that GA could offer a lot of new possibilities for solving these problems                                                                 |
| Savic & Walters (1997) | GA             | Development of GANET, and the application of GA for WDN design for minimization of cost of pipes | Benchmark WDN problems: Two-loop, Hanoi and New York Tunnel | The study inferred GA suitable for solving WDN design problems and performed better than LP, NLP, and enumeration methods                                                                                   |
| Dandy & Engelhardt (2001) | GA             | Application of GA for the rehabilitation of WDNs involving the replacement of water supply pipes for the minimization of reciprocal of system cost (capital, repair and damage cost) | EL103N Zone network of Adelaide city      | GA performed efficiently for solving rehabilitation problem which included increased complexities such as identifying solutions within budget limits and consideration of the diameter of replaced pipes as decision variables |
| Maier et al. (2003)   | ACO, GA        | Application of ACO and GA for WDNs and their performance, with the objective of minimization of total cost of WDNs | Two benchmark problems: 14-Pipe network, New York Tunnel WDNs | ACO algorithms outperformed GAs for the two case studies in terms of computational efficiency and their ability to find near global-optimal solutions                                                              |
| van Zyl et al. (2004)  | GA             | Development of a hybrid model by combining GA with a hill climber search method for minimization of cost of energy | Hypothetical WDN problem and a real WDN in the UK | The hybrid method performed significantly better than a GA method for the solution of WDN problems                                                                                                          |
| Vairavamoorthy & Ali (2005) | GA             | Use of pipe index vector as a measure of the relative importance of pipes in a network for reducing the search space and improving the efficiency of GA for minimization of capital cost | Alandur and Hanoi WDNs                  | Different pipes have various degrees of influence on the hydraulic performance of WDN. This information can be employed to reduce the search space and the efficiency of GA                                                                 |

(continued)
| Author(s) (year)       | Technique used        | Work and objectives                                                                 | Case studies/problems considered       | Key findings                                                                                     |
|------------------------|-----------------------|--------------------------------------------------------------------------------------|----------------------------------------|------------------------------------------------------------------------------------------------|
| Wu & Walski (2005)     | GA                    | Self-adaptive penalty approach for tuning the penalty factor and thus improving the   | Hanoi WDN                             | Self-adaptive penalty factor approach performed better than other constraint handling methods for GA, such as fixed, dynamic, annealing, niched and self-organizing penalty |
|                        |                       | efficacy of the model for minimization of cost and maximization of benefits            |                                        |                                                                                                |
| Keedwell & Khu (2005)  | GA                    | Proposed cellular automation for network design algorithm—Genetic Algorithm (CANDA-GA)| Two-loop, two industry networks        | CANDA-GA gave faster convergence of the algorithm and better solutions with the same computational efforts than traditional GA |
|                        |                       | approach for initial seeding of the GA algorithm and applied for WDN design with the  |                                        |                                                                                                |
|                        |                       | objective of minimization of cost                                                    |                                        |                                                                                                |
| Rao & Salomons (2007)  | GA                    | The combined use of ANN for predicting the consequences of different pump and valve   | Hypothetical WDN                       | The GA-ANN model has reduced the run time significantly when compared to the hydraulic simulation model and noted that the meta-modeling could help for large complex networks |
|                        |                       | control settings and GA for selecting the best combination of those settings to        |                                        |                                                                                                |
|                        |                       | minimize the energy cost of meeting the current and future demands                   |                                        |                                                                                                |
| Munavalli & Kumar (2003)| GA                   | Application of niched operator and creep mutation GA for optimal scheduling of        | Three example networks                 | The improved GA with the niched operator and creep mutation performed better than simple GA, as it produced quick optimal solutions and found well suited for multiple chlorine source problems |
|                        |                       | chlorine dosage (coded as binary strings) at water quality sources for minimization of|                                        |                                                                                                |
|                        |                       | the squared difference between the computed chlorine concentration and minimum        |                                        |                                                                                                |
|                        |                       | specified concentration                                                            |                                        |                                                                                                |
| Eusuff & Lansey (2003) | Shuffled Frog Leaping | Application of SFLA for WDN design problem for minimization of cost of pipes         | Two-loop, Hanoi, and New York Tunnel   | SLFA obtained the best solutions for Two-loop, and Hanoi, and near-optimal solutions for NYT problem. SLFA found optimal solutions in a lesser number of iterations compared to GA and SA |
|                        | Algorithm (SFLA)      |                                                                                        | (NYT) WDNs                             |                                                                                                |
| Geem (2006)            | Harmony search (HS)   | Application of HS for WDN design and comparison of results with other meta-heuristic   | New York Tunnel WDNs                   | HS was able to find the best solution with the least number of iterations when compared with GA, SA, TS, ACO, SFLA methods. The HS showed good convergence and reliability in achieving optimal solutions |
|                        | algorithm             | algorithms with the objective of minimization of cost of pipes                       |                                        |                                                                                                |
### Table 2 | continued

| Author(s) (year) | Technique used | Work and objectives | Case studies/problems considered | Key findings |
|------------------|----------------|---------------------|----------------------------------|--------------|
| Kadu et al. (2008) | Modified GA | Application of modified GA for WDN design problem with the objective of minimization of the cost of pipes | A hypothetical network, Hanoi, and TRN | Modified GA improves the efficiency and effectiveness of GA by reducing the search space, random use of various basic and additional GA operators |
| Cunha & Ribeiro (2004) | Tabu search algorithm | Application of Tabu search algorithms for WDN design problems for minimization of cost of pipes | Two-loop, Hanoi, and NYT | Promising results obtained by using the Tabu search algorithm for WDN design problem |
| Mohan & Babu (2010) | Honey-bee mating optimization (HBMO) | Application of HBMO for optimal WDN design and its comparison with other algorithms like GA and SA for minimization of cost of pipes | Two-loop and Hanoi WDNs | HMBO was able to arrive at optimal solutions in a lesser number of function evaluations compared to GA and SA. For HMBO, the uniform crossover preferred over the single/multi-point crossover. |
| Suribabu (2010) | DE | Application of DE for least-cost design of WDNs for minimization of cost of pipes | Two-loop, Hanoi, New York Tunnel, and 14 pipe network expansion problem | The DE found to be more efficient than GA and SA for the optimal design of WDNs. The role of randomness is less in DE as compared to other meta-heuristic algorithms |
| Vasan & Simonovic (2010) | DE | Development of DENET, by integrating DE and EPANET for WDN design problem for minimization of cost and maximization of network resilience (two separate cases) | New York Tunnel, Hanoi WDNs | DENET found to be a useful tool, which can be used as an alternative approach for solving WDN design problems |
| Shibu & Reddy (2014) | Cross entropy (CE) optimization | Application of CE method for optimal WDN design under demand uncertainty for minimization of cost | NYT and a real case study of Tukumzone, India | The CE method performed quite well for the design of WDNs and noted that the optimal cost goes on increasing with the increase in demand uncertainty |
| Sirsant & Reddy (2018) | Self-adaptive DE (SADE) | Application and performance evaluation of SADE for the deterministic and reliability-based design of WDNs considering cost minimization subject to satisfying a minimum reliability level | Two-loop, Apulian, BakRyan, Fossolo and a real WDN of Ramnagar zone in India | SADE performed well for both the deterministic and reliability-based designs of WDNs and converged faster than simple DE and other meta-heuristics methods with a higher success rate |
| Fallah et al. (2019) | Gravitational search algorithm (GSA) | Application of GSA for WDN design problem and results compared with those obtained using different EAs for minimization of cost of pipes | Hanoi, Two reservoir network and New York Tunnel and a real WDN situated in Khorraramshahr city in Iran | GSA converged faster for Hanoi and Khorraramshahr WDNs. For NYT and TR problems, GSA required a larger number of function evaluations compared to previous studies but led to lower-cost solutions. The GSA requires only two parameters |
**Table 3** | Applications of multi-objective evolutionary algorithms for the multi-objective design of water distribution systems

| Author(s) (year) | Technique used | Work and objectives | Case studies/problems considered | Key findings |
|------------------|----------------|---------------------|----------------------------------|--------------|
| Halhal et al. (1997) | Structured messy GA (SMGA) | Application of SMGA for solving multi-objective rehabilitation of WDNs for minimization of capital cost and maximization of benefits | Small-looped example network, real WDN in Morocco | The SMGA technique proved to be more efficient than traditional GA |
| Savic et al. (1997) | MOGA | Use of pump switching as a surrogate for maintenance cost, improvement of the traditional GA with hybridization involving a local search for minimization of energy and maintenance cost | Example WDN problem | Seeding of the initial population with solutions from previous runs brought improvements in both efficacy and quality of solutions found |
| Cheung et al. (2003) | SPEA | Application of SPEA for the multi-objective design of WDNs, by maintaining an external population for storing the non-dominated solutions from the beginning of the algorithm, for minimization of cost, minimization of the maximum deficit in pressure and maximizing the hydraulic benefits | Hypothetical WDN comprising of 14 pipes and 12 nodes | SPEA performed well for the problem. Uniform crossover was found to be most suitable. The recombination operator has a greater influence than the mutation operator on the results |
| Prasad et al. (2004) | NSGA-II | Investigation of the booster location and scheduling in WDNs for minimization of total disinfectant dosage and maximization of the volumetric demand | Utility located in the eastern USA | The model can determine the optimal locations of booster stations given the number of stations, does not require pruning of the monitoring locations as all the demand nodes modeled as monitoring nodes |
| Prasad & Park (2004) | NSGA-II | Introduction of the concept of network resilience as a surrogate for WDN reliability and its use for a multi-objective design for minimization of cost and maximization of network resilience | Two-loop and Hanoi WDN | The constraint domination criteria incorporated, thus enabling GA to handle the constraints more efficiently |
| Kapelan et al. (2005) | Robust NSGA-II (RNSGA-II) | Development and application of RNSGA-II (which considers the age of chromosome for calculating its fitness function) for minimization of cost and maximization of robustness | New York tunnel WDN | The RNSGA-II can handle any type of hydraulic uncertainty and model nonlinearity. The drawback is that it needs two additional parameters, minimum chromosome age and several samples, which require some tuning |

*(continued)*
Table 3 | continued

| Author(s) (year) | Technique used | Work and objectives | Case studies/problems considered | Key findings |
|------------------|----------------|---------------------|----------------------------------|--------------|
| Farmani et al. (2005) | NSGA-II and SPEA-II | Comparison of the performance of two EAs for the multi-objective design of WDNs for minimization of cost and minimization of maximum head deficiency | New York Tunnel and Hanoi | SPEA-II performed slightly better than NSGA-II and noted the need for further improvement to obtain better Pareto fronts |
| Vamvakeridou-Lyroudia et al. (2005) | MOGA | Multi-objective design of WDNs by incorporating fuzzy reasoning for the estimation of benefits considering minimization of cost and maximization of benefits | Anytown WDN | The multiple criteria applied for benefit function are more extensive and strict. Despite this, the model gave solutions that not only satisfy these criteria but also lead to reduced costs |
| Dandy & Engelhardt (2006) | MOGA | Application of MOGA for replacement scheduling of water pipelines for two cases: single time step and multiple time step considering minimization of economic cost and maximization of reliability | EL103N Zone network of Adelaide city | MOGA performed efficiently for the problem. However, a very simplified framework discussed in this study to solve the problem, such as the replacement of pipes with the same diameter pipe |
| Ostfeld & Salomons (2006) | NSGA-II | Optimal placement of sensors in WDN using the multi-objective formulation for minimization of the expected time of detection of contamination, projected population affected prior to detection, expected demand of contaminated water prior to detection, and maximization of detection likelihood | Two example WDNs | The presented approach can be applied to real case studies also. The main limitation is how to sample injection events more efficiently |
| Prasad & Tanyimboh (2008) | NSGA-II | Multi-objective design of WDNs considering tank design procedure (taking tank shape parameters as decision variables) using entropy and resilience as the surrogates for reliability, for minimization of cost and maximization of resilience and entropy (one at a time) | Anytown WDN | Entropy serves as a better surrogate for reliability. The hydraulic performance of the obtained least-cost solutions found to be satisfying all the hydraulic constraints |
| Jayaram & Srinivasan (2008) | NSGA-II | Introduction of a new index (MRI) as a surrogate for WDN reliability and its application for the multi-objective design of WDNs | A hypothetical network comprising of 14 pipes and 11 nodes | MRI could overcome the drawbacks of the resilience index in terms of its application to WDNs with multiple supply sources. Feeding NSGA-II with initial solutions using heuristic methods reduces the computational burden to a huge extent |
| Author(s) (year) | Technique used | Work and objectives | Case studies/problems considered | Key findings |
|-----------------|----------------|----------------------|---------------------------------|--------------|
| Raad et al. (2010) | AMALGAM | Comparison of four reliability indices as surrogates for reliability for the multi-objective design of WDNs for minimization of cost and maximization of four reliability indices: flow entropy, resilience, network resilience, and a modified reliability surrogate (MRS) | TRP, Hanoi, and NYT WDNs | Although no ‘best’ RSM was identified, network resilience and MRS showed comparatively better performance than other indices |
| Creaco et al. (2014) | NSGA-II | Comparison of resilience and entropy as reliability surrogate for the multi-objective design of WDNs for minimization of cost and maximization of reliability indices, entropy, and resilience (one at a time) | A hypothetical network consisting of 11 pipes and a real network of Ferrara city, Italy | Resilience index found to be a more suitable surrogate for reliability compared to entropy. Huge computational savings can be obtained by employing these indices in the design procedure |
| Patil et al. (2020) | MOPSO+ | MOPSO is augmented with (1) local search, (2) a modified strategy for assigning the leader and (3) a modified mutation scheme termed as MOPSO+ and employed for WDN design for minimization of cost and maximization of network resilience | Hanoi, Blacksburg, New York Tunnel, GoYang WDNs | A significant number of new Pareto-optimal solutions obtained using MOPSO+ compared to previous studies. For medium-sized networks, the number of function evaluations was the same as that of previous studies, but for intermediate-sized problems, more number of function evaluations needed, but the solutions obtained were better The suitability of MOPSO+ still needs to be tested for larger sized networks |
| Sirsant & Reddy (2020) | NSGA-II | The study applied extended period simulation (EPS) and NSGA-II for the multi-objective optimization of WDNs with maximization of reliability or reliability surrogate measure (RSM) and minimization of cost as two objectives. Investigated alternatives for computationally intensive reliability procedures, and evaluated the efficacy of RSMs like entropy, resiliency, and network resilience, and their combinations to represent the reliability of WDNs | Case studies of Two-loop, GoYang, and Fossolo WDNs, as well as a real case study of Ramnagar zone WDN in India | NSGA-II provides effective Pareto-optimal solutions for the bi-objective WDN model, which helps to find the associations between RSMs and the reliability of WDNs. The study recommended entropy as a surrogate for mechanical reliability (for larger WDNs), while resiliency for hydraulic reliability; and a combined entropy-resilience index (CERI) for accounting both hydraulic and mechanical reliabilities |
Applications in reservoir operation and irrigation systems

Reservoirs and irrigation systems need to be operated in a cost-effective manner such that the deficits are minimum as well the benefits achieved in terms of minimum cost or maximum energy production. Thus, the optimization problem is formulated as determination of the optimal release or operating policies such that the deficits are minimum and the benefits are maximum. Several meta-heuristic techniques were applied to solve different problems (Rani & Moreira 2010). To solve single-objective problems, the techniques used include GA (Oliveira & Loucks 1997; Wardlaw & Sharif 1999; Nixon et al. 2001; Merabtene et al. 2002; Dessalegne et al. 2004; Raju & Kumar 2004; Kerachian & Karamouz 2006, 2007; Kumar et al. 2006; Kuo et al. 2006; Zahraie et al. 2008), Shuffled complex evolution (SCE) algorithm (Lerma et al. 2015), PSO (Kumar & Reddy 2007; Reddy & Kumar 2007a; Ghimire & Reddy 2013); for solving multi-objective problems, the MOGA (Reddy & Kumar 2006), elitist-mutated MOPSO (Reddy & Kumar 2007b, 2009), multi-objective DE (MODE, Reddy & Kumar 2007c, 2008; Raju et al. 2012), etc. More details of these applications are described in Table 5.

Applications in water supply and wastewater system

The water supply and wastewater systems are subjected to many dynamic loadings, such as rain, the release of stormwater from storage tanks, etc. These loadings need to be regulated efficiently such that the required flow quality and quantity levels are maintained at minimum costs. There were several studies that have used EAs for solving these problems, such as GA (Rauch & Harremoes 1999; Tsai & Chang 2001; Wang & Jamieson 2002; Lavric et al. 2005; Murthy & Vengal 2006; Montaseri et al. 2015; Swan et al. 2017; Raseman et al. 2020), SFLA (Chung & Lansey 2009), etc. Also, for considering different conflicting issues, such as minimizing the total system cost and satisfactory performance of the systems under different dynamic loadings or contaminant additions, multi-objective optimization models developed and engaged MOEAs to solve the problems like MOGA (Chen et al. 2003), NSGA-II (Guria et al. 2005; Yandamuri et al. 2006; Fu et al. 2008; Muschalla 2008), etc. Table 6 gives more details of the applications and findings of the studies.

Applications in watershed management and fluvial systems

Watershed management and planning require modeling the hydrologic and fluvial characteristics properly and efficiently, such that the required water management conditions can be achieved in a cost-effective manner. Thus, the various watershed management techniques, such as the design of detention systems, flood management practices, and other best management practices (BMPs), need to be designed considering cost minimization and system reliability and efficiency maximization. Several studies used EAs for solving the relevant optimization models like GA (Harrell & Ranjithan 2003; Muleta & Nicklow 2005; Artita et al. 2015; Aminjavaheri & Nazif 2018), DE (Hang & Chikamori 2017), PSO (Shamsudin et al. 2014), MOGA (Yeh & Labadie 1997; Perez-Pedini et al. 2005), NSGA-II (Lee et al. 2012; Karamouz & Nazif 2013; Aminjavaheri & Nazif 2018), etc. More details of the applications and their findings are given in Table 7.
### Table 4 | Applications of EA and SI meta-heuristic methods for optimization of urban drainage and sewer systems

| Author(s)                | Technique used                | Work and objectives                                                                 | Case studies/problems considered | Key findings                                                                                                                                                                                                 |
|-------------------------|-------------------------------|----------------------------------------------------------------------------------------|----------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Walters & Lohbeck (1993)| GA                            | Optimal layout design of the network using GA for minimization of cost                 | Example network                  | GA model with integer coding proved to be very efficient compared to binary-coded GA. The computational and memory requirements for GA found to be very less as compared to DP                                               |
| Walters & Smith (1995)  | GA                            | Optimal layout design using evolutionary and GA principles for minimization of cost. The use of an efficient tree growing algorithm and incorporation of redundant genetic information within the reproduction phase | Example network                  | The algorithm found to be highly efficient and is suitable for those networks which have one or more identifiable roots from which flow diverges or to which flow converges.                                           |
| Liang et al. (2004)     | GA and Tabu search            | Application of GA and Tabu search techniques for the design of gravity waste water collection systems for minimization of direct cost (material, backfill, excavation, and soil dump cost) | Example network                  | Both GA and TS produced optimal designs with shallower pipe elevations downstream compared with traditional design. TS technique lead to lower-cost designs than GA                                                   |
| Afshar et al. (2006)    | GA                            | Hydrograph-based sewer design using GA as the optimization tool and SWMM as the hydraulic simulator for minimization of total piping and excavation cost | Two example networks             | The proposed model proved to be very efficient as it could incorporate the inflow hydrograph as an input to the system and perform flood routing and is suitable for application to large-scale stormwater networks |
| Barreto et al. (2006)   | NSGA-II and ε-MOEA            | Multi-tier approach for solving the problem of drainage network rehabilitation for minimization of pipe installation cost and minimization of surcharge in a pipe network | Two example networks             | NSGA-II performs better than ε-MOEA for small population size, but its performance degrades with an increase in population size. The performance of ε-MOEA showed less sensitivity to population size |
| Guo et al. (2006)       | CA-GASiNO                     | Application of a hybrid CA-GASiNO method which involves seeding the MOGA with local search based on CA principle for Sewer Network Optimization, with minimization of flooding within the sewer system and minimization of the capital cost of the network as two objectives | One small hypothetical network and one large real network | The CA-GASiNO required comparatively much smaller number of function evaluations as compared to NSGA-II                                                                                                           |
| Author(s) (year) | Technique used | Work and objectives | Case studies/problems considered | Key findings |
|-----------------|----------------|---------------------|---------------------------------|-------------|
| Muleta & Boulos (2007) | NSGA-II | Application of NSGA-II for the multi-objective design of urban drainage systems by coupling it with EPA SWMM5 for minimization of cost and overflow volume | A hypothetical case study | The tool performed well for the example problem and can be useful to any wastewater utility attempting to optimize its capital improvement program |
| Barreto et al. (2010) | NSGA-II and ε-MOEA | Application and performance evaluation of two EAs for the rehabilitation of urban drainage systems for minimization of rehabilitation cost (cost of pipes, excavation, installation, restoration, and reinstatement) and minimization of flood damage cost | An example network consisting of 12 pipes, 13 manholes, and 11 sub-catchments | NSGA-II performed better for smaller population sizes, but its performance deteriorates for large population sizes; ε-MOEA was less sensitive to population size. However, the diversity of solutions not as good as that of NSGA-II for large population sizes. The number of function evaluations and computational time were better for NSGA-II |
| Penn et al. (2013) | NSGA-II | A multi-objective optimization model for estimating the optimal distribution of different types of GWR homes in an existing municipal sewer system for minimization of wastewater flow at the outlet of the neighborhoods sewer system and minimization of the cost of the on-site GWR treatment system | Sewer system located in central Israel, near the coast (flat terrain) | The results obtained lead to maximum water savings in most houses. Further suggested consideration of the water quality aspect in future studies |
| Karovic & Mays (2014) | SA | Development of an optimization procedure for designing storm and sanitary sewer systems using SA for minimization of cost | A hypothetical storm sewer system | Better results obtained by applying the SA procedure rather than the straight slope method, implying that optimization procedures should be used for designing the sewer systems |
| Vojinovic et al. (2014) | NSGA-II | Multi-objective design of urban drainage systems under uncertainties from climate change, urbanization, population growth, and aging of pipes considering minimization of damage cost and intervention cost | Case study of Dhaka, Bangladesh | The NSGA-II method produced widespread Pareto-optimal solutions for urban drainage systems |
| Yazdi et al. (2017a) | Non-dominated sorting Harmony Search (NSHS) | Development and application of NSHS for assigning optimal rehabilitation plans for sewer pipe networks. Three optimization tools, NSGA-II, MOPSO, and NSHS, were applied and tested for the problem for minimization of pipe replacement cost and flooding overflow volume | A storm sewer pipe network in the south part of Seoul, South Korea | The NHSH gave the best results for all population sizes considered, whereas MOPSO performed the worst for all the cases. NSGA-II gave solutions closer to the NSHS algorithm when the number of function evaluations increased, NSHS still performed better |

(continued)
Applications in parameter estimation of hydrological models

For simulating the various hydrological processes, there exist several hydrological models (namely, lumped, semi-distributed, distributed models). The model may consist of a large number of components with several parameters, so one has to choose the appropriate model depending on the purpose and accuracy of the model variables of interest. To represent and simulate various hydrological processes accurately, it may require proper calibration and validation of the model parameters using historical data. A typical calibration process thus requires minimization of the error between the model simulated and actual values of the hydrologic variables (e.g., runoff). Sometimes, the model responses vary and may be suitable for a particular event or application. Also, the different performance indices used for the calibration process may give different results. For improving the performance of the simulation models under different scenarios, multi-variate calibration may be needed, which can be done using multi-objective calibration. For calibration of the hydrological models, several studies used different EAs like GA (Wang 1991; Franchini & Galeati 1997; Liong et al. 2001; Zou & Lung 2004), SCE algorithm (Zhang et al. 2009; Tigkas et al. 2016; Krishnan et al. 2018; Shin & Choi 2018), MOPSO (Mostafaie et al. 2018), NSGA-II (Khu & Madsen 2005; Alamdari et al. 2017; Tian et al. 2019), AMALGAM (Koppa et al. 2019), etc. More details of EAs and MOEA applications for single and multi-objective parameter estimation of hydrological models are presented in Table 8.
### Table 5 | Applications of EA and SI meta-heuristic methods for the operation of reservoirs and irrigation systems

| Author(s) (year)      | Technique used | Work and objectives                                           | Case studies/problems considered | Key findings                                                                                                                                                                                                                                                                                                                                 |
|-----------------------|----------------|---------------------------------------------------------------|-----------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Oliveira & Loucks    | GA             | Application of GA for multi-reservoir operation considering minimization of the sum of squared deficits | Two hypothetical systems          | GA proved to be an efficient tool for solving the multi-reservoir operation problem and can handle complex situations like side demands or constraints on releases, power production as compared to the DP approach                                                                                                                                                                       |
| Wardlaw & Sharif     | GA             | Different alternative formulations of GA evaluated for the four reservoir problem for maximization of the benefits | Hypothetical four reservoir problem | A real-value representation, incorporating tournament selection, elitism, uniform crossover, and modified uniform mutation will operate most efficiently for the reservoir operation problem. GA found to be more efficient than traditional methods like DP and has the advantage that no initial trial release policy required                                                                                      |
| Nixon et al.         | GA             | Examination of GA optimization to identify water delivery schedules for an open channel irrigation system for minimization of the number of orders shifted and minimization of channel flow rate variations, such that particular size of order shifts encouraged, and others discouraged, and channel capacity not exceeded | A problem involving scheduling irrigation water deliveries in a single channel spur consisting of five irrigators with one order each | GA performed well and found to be suitable for efficiently scheduling irrigation orders                                                                                                                                                                                                                                    |
| Merabtene et al.     | GA             | Development of a DSS to assess the susceptibility of water supply systems to droughts. GA used to search the optimal operation, such that drought risk index is minimum | Fukuoka city water supply system, Japan | GA performed well for the problem, but the physical attributes of the problem can be further incorporated using engineers' experience through fuzzy inference                                                                                                                                                         |
| Raju & Kumar          | GA             | Application of GA to evolve efficient cropping pattern for maximizing benefits for an irrigation project | Sri Ram Sagar Project (SRSP) situated on river Godavari in Telangana, India | GA is found to be a useful tool for irrigation planning and can even be applied for complex problems involving nonlinear optimization (continued)                                                                                                                                                                                                     |
| Author(s) (year) | Technique used | Work and objectives | Case studies/problems considered | Key findings |
|------------------|----------------|---------------------|----------------------------------|--------------|
| Dessalegne et al. (2004) | GA | Evaluation and optimization of dam operations in multi-reservoir river systems for minimization of the maximum water surface elevation deviation at any cross-section and over any incremental time step, and minimization of the maximum rate of water level fluctuation at any cross-section over the entire simulation horizon | A hypothetical three-reservoir river system and a portion of the Illinois River Waterway | GA performed efficiently for both the case studies, and the methodology can be further extended to optimize the operation of multiple reservoir systems and to meet environmental requirements as well |
| Kuo et al. (2006) | GA | Development of a hybrid ANN-GA model for reservoir water quality management, with ANN serving as the model for predicting the phosphorus concentrations and GA for determining the proper reduction rates of nutrient loads from the watershed to minimize the phosphorus reduction rate of the inflow | Feitsui Reservoir situated in Taipei Metropolitan Area | The hybrid model performed efficiently by significantly reducing the computational burden as required in case of other simulation models |
| Kumar et al. (2006) | GA | Development of a GA-based model for obtaining an optimal operating policy and optimal crop water allocation from an irrigation reservoir for maximization of the sum of the relative yields from all crops in the irrigated area | Malaprabha single-purpose irrigation reservoir in Karnataka State, India | The performance of the GA model was found to be suitable for application on real case studies |
| Kumar & Reddy (2006) | ACO, GA | Evaluation of ACO for the derivation of optimal operation policies for multi-purpose reservoir system, considering short-time and long-time horizons | Case study of Hirakud reservoir system, India | The ACO technique has resulted in superior performance for long-term reservoir operation as compared to GA solutions |
| Reddy & Kumar (2006) | MOGA | Application of MOGA for multi-purpose reservoir operation for minimization of the sum of squared deficits and maximization of annual energy production | Real case study of Bhadra reservoir system in India | MOGA performed well and generated good Pareto-optimal solutions for the reservoir operation problem |
| Kumar & Reddy (2007) | Elitist-mutated PSO (EMPSO), GA | Development of EMPSO and its application for multi-purpose reservoir operation considering minimization of the sum of squared deficits for irrigation, and maximization of annual energy production | Hypothetical four reservoir system and real case study of the Bhadra reservoir system in India | The EMPSO consistently performed better than standard PSO and GA techniques, requiring less number of function evaluations |
Table 5 | continued

| Author(s) (year)          | Technique used | Work and objectives                                                                 | Case studies/problems considered | Key findings                                                                 |
|---------------------------|----------------|--------------------------------------------------------------------------------------|----------------------------------|-------------------------------------------------------------------------------|
| Reddy & Kumar (2007a)     | EMPSO, GA      | Elitist-mutated PSO (EMPSO) proposed for integrated reservoir operation for irrigation and multi-crop water allocation in a reservoir command area. The model considers maximizing crop yields with due consideration of water shortages in different periods | Case study of Malaprabha reservoir system in India | The proposed PSO technique gave efficient solutions to obtain reservoir operation policies and crop water allocations for multiple crops. The approach found to be beneficial for integrated water management under water-scarce conditions |
| Reddy & Kumar (2007b)     | EM-MOPSO, NSGA-II | Development of EM-MOPSO for multi-objective multi-purpose reservoir operation for minimization of the sum of squared deficits for irrigation, and maximization of annual hydropower production | Four test problems and a real case study of the Bhadra reservoir system in India | The EM-MOPSO found to be an efficient tool for multi-objective reservoir operation and produced consistently better Pareto-fronts with good convergence and uniformly widespread solutions as compared to NSGA-I |
| Reddy & Kumar (2007c)     | MODE, NSGA-II  | Application of MODE for multi-objective multi-purpose reservoir operation for minimization of the sum of squared deviations for irrigation and maximization of annual hydropower production | Hirakud reservoir project in Orissa state, India | The MODE performed better than NSGA-II for reservoir operation problem. Noted that MODE could serve as an efficient alternative tool for solving multi-objective optimization problems in the water resource systems |
| Kerachian & Karamouz (2006), 2007 | Variable Length Chromosome GA (VLGA) | The SGA and VLGA were used to reduce the computational burden of GA and applied for reservoir operation problem accounting for inherent uncertainties in reservoir inflows considering maximization of the utility function of different water users | 15-Khordad Reservoir in the central part of Iran | The SGA reduced the overall time as compared to GA by dynamically updating the chromosome length. VLGA was found to be an efficient tool for solving the problem and can be even applied to problems comprising longer planning horizons |
| Zahraie et al. (2008)     | VLGA           | Reservoir operation using two adaptive varying chromosome lengths GA (VLGA) for maximization of the utility function of different water users | Zayandeh-Rud Reservoir, Karoon-I Reservoir, and the system of Bakhtiari and Dez reservoirs in series in Iran | The VLGA found to be efficient in solving the reservoir operation problem |
| Reddy & Kumar (2008)      | MODE           | Proposed MODE to evolve different strategies for the simultaneous evolution of optimal cropping pattern and operation policies for irrigation reservoir system with the objectives of maximizing the total net benefits from the irrigation system and maximize the total irrigated area in the command area | Real case study of Malaprabha reservoir systems in India | MODE approach provides a wide spectrum of efficient Pareto-optimal solutions and gives sufficient flexibility to select the best irrigation planning and reservoir operation plan, which could be very useful for multi-crop irrigation reservoir systems |
The purpose of the GW monitoring networks is to capture the information about the contamination of GW and its source/location. In order to design a cost-effective system, the number of monitoring wells should be minimum and should not be redundant while being able to capture the desired information about the contamination. Different types of EAs were used for solving the groundwater systems and monitoring network design models formulated with different complexities. The popular techniques used include GA (McKinney & Lin 1994; Ritzel et al. 1994; Chadalavada & Datta 2008), SA (Dougherty & Marryott 1991), DE (Alizadeh et al. 2018), Probabilistic Pareto GA (PPGA; Luo et al. 2016), NSGA-II (Tang et al. 2007), ε-multi-objective noisy memetic algorithm (ε-MONMA; Song et al. 2019), etc. More details of the applications of EAs for groundwater systems are given in Table 9.

Groundwater systems are redundantly subjected to various pollutants at different times and locations, which are dynamic in nature. In order to ensure that the required GW quality levels are maintained, observation, as well as pumping wells, need to be designed. The problem can thus be formulated as determining the location and number of wells as well as the required pumping rates at these wells such that the cost is minimum and the desired quality levels are maintained. Several studies used EAs for solving the groundwater remediation problems via the simulation-optimization framework such as GA (Huang & Mayer 1997; Wang & Zheng 1997; Sun & Zheng 1999; Smalley et al. 2000; Yoon & Shoemaker 2001; Zheng & Wang 2002; Babbar & Minsker 2006; Wu et al. 2006; Park et al. 2007; Bayer et al. 2008; Seyedpour et al. 2019), SA (Kobayashi et al. 2008); MOGA (Erickson et al. 2002; Mantoglou & Kourakos 2007; Singh et al. 2008), NSGA-II (Singh & Chakrabarty 2011; Ouyang et al. 2017), etc. More details of these EAs applications are also elaborated in Table 9.

### Table 5 | continued

| Author(s) (year) | Technique used | Work and objectives | Case studies/problems considered | Key findings |
|------------------|----------------|---------------------|---------------------------------|--------------|
| Reddy & Kumar (2009) | MODE, NSGA-II | Integrated water resource management model for reservoirs considering minimization of squared irrigation deficits and maximization of hydropower for reservoir system, subject to meeting the flood control regulations | Hirakud reservoir system in India | MODE helps in generation of efficient Pareto-optimal solutions and helps to analyze the trade-offs between multiple objectives, thus facilitated easiness in the decision making for the operator |
| Raju et al. (2012) | MODE | Application of MODE for irrigation planning for maximization of net benefits, agricultural production, and labor employment | Mahi Bajaj Sagar Project, Rajasthan, India | MODE performed well for the problem. Further noted that while applying for real case studies, proper sensitivity analysis should be carried out to determine the best-suited parameters |
| Lerma et al. (2015) | Shuffled complex evolution (SCE-UA) and Scatter search algorithm | Assessment of two EAs to design the optimal operating rules for water resource systems for minimization of the cost of water storage, and costs associated with a deficit of demands | Tirso-Flumendosace-Campidano system located on the island of Sardinia (Italy) | SCE-UA found to be a more efficient algorithm for solving the problem in terms of faster convergence and attaining global optimality |

Applications in groundwater remediation, groundwater systems monitoring network design

The purpose of the GW monitoring networks is to capture the information about the contamination of GW and its source/location. In order to design a cost-effective system, the number of monitoring wells should be minimum and should not be redundant while being able to capture the desired information about the contamination. Different types of EAs were used for solving the groundwater systems and monitoring network design models formulated with different complexities. The popular techniques used include GA (McKinney & Lin 1994; Ritzel et al. 1994; Chadalavada & Datta 2008), SA (Dougherty & Marryott 1991), DE (Alizadeh et al. 2018), Probabilistic Pareto GA (PPGA; Luo et al. 2016), NSGA-II (Tang et al. 2007), ε-multi-objective noisy memetic algorithm (ε-MONMA; Song et al. 2019), etc. More details of the applications of EAs for groundwater systems are given in Table 9.

Groundwater systems are redundantly subjected to various pollutants at different times and locations, which are dynamic in nature. In order to ensure that the required GW quality levels are maintained, observation, as well as pumping wells, need to be designed. The problem can thus be formulated as determining the location and number of wells as well as the required pumping rates at these wells such that the cost is minimum and the desired quality levels are maintained. Several studies used EAs for solving the groundwater remediation problems via the simulation-optimization framework such as GA (Huang & Mayer 1997; Wang & Zheng 1997; Sun & Zheng 1999; Smalley et al. 2000; Yoon & Shoemaker 2001; Zheng & Wang 2002; Babbar & Minsker 2006; Wu et al. 2006; Park et al. 2007; Bayer et al. 2008; Seyedpour et al. 2019), SA (Kobayashi et al. 2008); MOGA (Erickson et al. 2002; Mantoglou & Kourakos 2007; Singh et al. 2008), NSGA-II (Singh & Chakrabarty 2011; Ouyang et al. 2017), etc. More details of these EAs applications are also elaborated in Table 9.
| Author(s) (year) | Technique used | Work and objectives | Case studies/problems considered | Key findings |
|-----------------|-----------------|---------------------|---------------------------------|--------------|
| Rauch & Harremoes (1999) | GA | A novel approach to control the whole system of the sewer system, treatment plant, and receiving water, with the aim to achieve minimum effects of pollution, considering minimization of the overflow volume as objective | A hypothetical example | The application of predictive model control in conjunction with genetic algorithms offers an attractive tool for real-time control of urban wastewater systems |
| Tsai & Chang (2001) | GA | Development of a mathematical programming model for water usage and treatment network design for minimization of operating cost and freshwater consumption rate | Two example problems | Search space was reduced significantly by using split fractions as decision variables The appropriate ranges of the design variables were efficiently determined by cascading the evolution processes according to the inducing parameters |
| Wang & Jamieson (2002) | GA | Development of methodology for water quality management on a river basin scale based on GA/ANN approach for minimization of cost of treatment and conveyance of wastewater | Upper River Thames Basin, England | The proposed approach has several advantages in terms of incorporation of both construction and operating costs, rapid convergence, and vast progress in computational efficiency |
| Chen et al. (2003) | MOGA | Development of a hybrid control algorithm integrating the indiscernibility capability of rough set theory and search capability of genetic algorithms with conventional neural-fuzzy controller design and its application for minimization of the operating cost of wastewater treatment | Example problem | The hybrid fuzzy control system provides immediate guidance and control with respect to multi-objective requirements for distributed control system using on-line process data |
| Lavric et al. (2005) | GA | Application of GA for finding the optimum water resource allocation and the wastewater network for minimization of the supply water consumption | An example network | The algorithm guarantees both the optimal topology of the units’ operation network and the minimum supply water consumption |
| Guria et al. (2005) | NSGA-II | Application of NSGA-II for optimization of Reverse Osmosis (RO) desalination units using different adaptations of NSGA-II for maximization of the permeate throughput, minimization of the cost of desalination, and minimization of the permeate concentration | Operation of an existing plant and design of a new plant | NSGA-II and other schemes were used to obtain the optimal solutions and noted that the NSGA-II variant found to be producing good solutions |

(continued)
| Author(s) (year) | Technique used | Work and objectives                                                                 | Case studies/problems considered         | Key findings                                                                 |
|-----------------|----------------|--------------------------------------------------------------------------------------|------------------------------------------|------------------------------------------------------------------------------|
| Yandamuri et al. (2006) | NSGA-II      | A multi-objective optimization framework for optimal waste load allocation in rivers for minimization of total treatment cost and maximization of overall performance | Willamette river system in the state of Oregon | Results indicated that the least inequity Pareto-optimal solution demands significantly more treatment effort and cost compared with that of the least-cost Pareto-optimal solution |
| Murthy & Vengal (2006) | GA           | Application of GA for optimization of RO system for maximization of the rejection of the solute while varying the feed flowrate and the overall flux across the membrane | Case study of the RO system | GA converged quickly to the optimal solution and showed its suitability for the RO problem |
| Fu et al. (2008) | NSGA-II       | Application of NSGA-II for multi-objective optimal control of urban wastewater systems considering maximization of DO and Ammonia concentration in the river | An integrated case study was taken from literature | NSGA-II was able to generate good Pareto-optimal solutions for the chosen problem successfully |
| Muschalla (2008) | Adaptive NSGA-II | Development of a new multi-objective EA combining the advantages of NSGA-II and self-adaptive evolution strategies for optimization of the performance of an urban wastewater system considering minimization of investment cost and maximization of river water quality | The sewer system of Heusenstamm, located in the central part of the catchment of the river Bieber | The developed tool found to be robust and efficient in providing Pareto-optimal solutions. Further, it suggested focusing more on improving the computational efficiency of the model |
| Chung & Lansey (2009) | Shuffled Frog Leaping Algorithm (SFLA) | Application of SFLA for the optimization of a large-scale water supply system for minimization of the total cost (construction and expansion, and operations and maintenance costs for all components of pipes, canals, pumps, and treatment facilities) | A first system was comprised of a single water and wastewater plants, multiple sources (imported water, groundwater aquifer, and surface water) and two demands centers (domestic and agricultural) A second system comprising of six users – three domestic areas, one industrial, one agricultural, and one large outdoor area – and three wastewater treatment plants | The SFLA was able to generate good solutions for both the problems |
DISCUSSION

Meta-heuristics for decision making?

The wide range of the above applications shows that meta-heuristics is an emerging research area for solving a variety of water resources problems. There is also a growing interest for integrated water resources management frameworks, where the conventional disciplinary boundaries in water resources need to be reconsidered, and future management frameworks have to address different complexities that may arise due to high nonlinearities, a wider range of uncertainties, integration of large system components, etc. These issues pose significant challenges and motivate the need for EAs applications to advance adaptive decision making under uncertainty. Also, it is important to
| Author(s) (year)       | Technique used | Work and objectives                                                                 | Case studies/problems considered  | Key findings                                                                                                                                 |
|-----------------------|----------------|-------------------------------------------------------------------------------------|-----------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------|
| Yeh & Labadie (1997)  | MOGA           | Application of MOGA for multi-objective watershed-level planning of stormwater detention systems for minimization of detention system cost, sediment loading, providing supplemental water supply, and maximizing system reliability | Upstream branch of Pazam River in southern Taiwan | Successive Reaching Dynamic Programming (SRDP) can lead to trade-off solutions between detention system cost and detention effect by executing the algorithm for a range of discrete values of maximum flow. However, MOGA can generate trade-off solutions for multiple objectives much more efficiently |
| Harrell & Ranjithan (2003) | GA            | Planning and design of detention ponds by considering land management as well as decisions on pond location and sizes considering minimization of the cost of pond and maximization of removal efficiency | City Lake watershed in High Point, NC | The integrated planning and design of ponds found more cost-effective than setting one performance and site conditions for all the ponds. Incorporating land-use allocation associated with future growth can lead to lower-cost designs. The GA-based method flexible to allow the incorporation of more complex simulation models to estimate pollutant loading and removal |
| Muleta & Nicklow (2005) | GA and SPEA    | Integration of GA and SPEA with SWAT, and replacement of the SWAT simulations with ANN, considering minimization of erosion and sediment yield or maximization of net agricultural profit (for single-objective formulation); and minimizes erosion and sediment yield while simultaneously maximizing individual farm-based income that accrues from growing corresponding crops (for multi-objective formulation) | Big Creek watershed, Southern Illinois | Replacement of SWAT by ANN results in 84% reduction in computational time required. ANN model trained using hybrid EP and BP algorithms was found to be more efficient and effective than EP or BP alone |
| Perez-Pedini et al. (2005) | MOGA          | Distributed hydrologic modeling of an urban watershed and combined with GA to determine the optimal location of infiltration-based best management practices (BMPs), for minimization of project cost and watershed flooding | Aberjona River watershed, Massachusetts | The study found 20% reduction in the watershed peak flow by the application of BMPs to fewer than 200 HRUs (1 HRU = 120 × 120 m plot). An incremental approach targeting the more critical areas at initial stages and less critical areas in the future can be practised, as the optimal locations of only a few BMPs can be a subset of the optimal locations of a much larger set of BMPs |

(continued)
| Author(s) (year) | Technique used | Work and objectives | Case studies/problems considered | Key findings |
|-----------------|----------------|---------------------|---------------------------------|--------------|
| Lee et al. (2012) | Scatter search and NSGA-II | Development of System for Urban Stormwater Treatment and Analysis Integration (SUSTAIN) and its application for the watershed-scale design of stormwater BMPs, for minimization of the cost | An urban watershed in Kansas City, USA | SUSTAIN was found to be a useful tool which can be applied by various practitioners, municipalities, and watershed groups at the regional and local levels to address diverse management practice planning questions in a wide range of conditions |
| Karamouz & Nazif (2013) | NSGA-II | Development of a multi-criteria optimization model to select BMPs for flood management in urban watershed systems considering climate change, considering minimization of flood volume and maximization of the drainage system’s reliability | An urban watershed located in the north-eastern part of Tehran, the capital of Iran | The optimization results show that the cost of BMP development is a governing factor in system reliability and expected flood damage assessment. A small change in BMP cost and their application scheme may result in significant improvements in system operation |
| Artita et al. (2013) | Species Conserving Genetic Algorithm (SCGA) | Integration of the semi-distributed watershed model, Soil and Water Assessment Tool (SWAT) and SCGA for minimization of the total cost of BMPs | Watershed in southern Illinois | SCGA-SWAT is found to be an efficient tool for solving watershed planning and management problem. Further developments may include maintenance cost and land-use decisions |
| Shamsudin et al. (2014) | PSO | The study concerns detention ponds based on best management practices for the treatment and control of urban stormwater. Analytical Probabilistic Models (APM) and PSO method were used to develop the optimal combination of pond volume and outflow that yield the minimum cost | The case study area of Kuala Lumpur in Malaysia | The comparison of the results of PSO with APM showed that the PSO is more accurate as it does not need discretization of outlet size and found to be more robust, computationally cheaper and faster to implement |
| Hang & Chikamori (2017) | DE, ES | DE and ES approach applied to the calibration of the long- and short-term runoff model (LST model) to simulate the daily rainfall-runoff process. The study used three objective functions of the Nash–Sutcliffe efficiency coefficient, root mean square error, and mean absolute error, for evaluating the simulation accuracy of the LST model | Case study of the Be River catchment located in southern Vietnam | DE technique found to give slightly better performance and more stable solutions than those found by the ES technique during both calibration and validation periods |

(continued)
identify the problem properties across the different water resources field domains (such as watersheds, surface water, groundwater, reservoirs, water supply, etc.) that are posing computational barriers for large-scale water resources systems. There is a greater need to engage meta-heuristics-based optimization frameworks for improved decision making in water resources management.

Advantages of EAs as compared with conventional methods of optimization

While applying for practical problems, the EAs offer several benefits that include conceptual simplicity, flexibility, and robust response to changing environments and their ability to self-adapt the search for optimum solutions on the evolution. EAs have broad applicability, since, with the same procedure, they can be applied to any problem that can be expressed as a function optimization task (e.g., discrete combinatorial problems, continuous-valued parameter optimization problems, mixed-integer problems, and others). In contrast, the conventional techniques might be applicable only to continuous values or other restrictions on constrained sets. Many times, the objective or response surfaces modeled in practical problems are often multi-modal, and the conventional gradient-based approaches rapidly converge to local optima, which may return unsatisfactory performance. For simpler problems, where the response surface is strongly convex, the EAs do not perform as well as traditional optimization methods (e.g., gradient-based methods are designed to take advantage of the convex property of surface). EAs offer significant advantages for real-world problems with multi-modal functions. Also, in case of applying LP method to problems with non-linear objectives and/or constraints, which offers an almost certainly incorrect solution because of the simplifications or assumptions required for the technique. In contrast, EAs can directly incorporate any kind of arbitrary objectives and constraints. Also, the conventional methods of optimization are not robust to dynamic changes in the environment and often require a complete restart to provide a solution (such as DP technique). In contrast, EAs can be used to adjust solutions

| Author(s) (year) | Technique used | Work and objectives | Case studies/problems considered | Key findings |
|------------------|----------------|---------------------|---------------------------------|--------------|
| Aminjavaheri & Nazif (2018) | GA, NSGA-II | The study used GA and NSGA-II, along with SWMM and Management Option Rank Equivalence (M four parameters including the urban percent imperviousness, the depression storage of pervious surfaces, the curve number, and the Manning’s roughness coefficient of conduits are the most effective parameters ORE) approach to develop the robust optimal set of BMPs for urban runoff quantity management in data-poor catchments. The three objective optimization model consists of minimizing the outfall runoff volume, minimizing the BMP costs, and minimizing the system vulnerability | The urban basin located in the north of Tehran, Iran | After modeling the study area in the SWMM model, the most effective parameters were determined using the LH-OAT sensitivity analysis and found that four parameters of urban percent imperviousness, the depression storage of pervious surfaces, the curve number, and the Manning’s roughness coefficient of conduits were the most effective parameters in calibration. The proposed MORE approach helps to manage the urban surface runoff optimally in a way that the flood damage potential is minimized by the minimum cost |
| Author(s) (year) | Technique used | Work and objectives | Case studies/problems considered | Key findings |
|-----------------|----------------|---------------------|---------------------------------|--------------|
| Wang (1991)     | GA             | Application of GA for calibration of a conceptual rainfall-runoff model for minimization of the sum of squares of differences between computed and observed discharge | Xinjiang rainfall-runoff model for the Bird Creek catchment data | GA performed efficiently for the problem, attaining a global peak 8 times out of 10 trial runs |
| Franchini & Galeati (1997) | GA, Pattern Search (PS) | Analysis of various GA schemes (varying in terms of the mutation and crossover operators) and their robustness and efficiency for calibration of conceptual rainfall-runoff model for minimization of the RMSE between the observed and model-simulated flow values | An 11 parameter distributed model (ADM) | The parameterization of GA does not create any major difficulties, thus making GA a robust algorithm. The PS method performed slightly better than all the GA schemes involved and consumed less computational time compared to GA |
| Liong et al. (2001) | Accelerated Convergence GA (ACGA) | Development of a hybrid GA-NN tool for generating Pareto-optimal solutions of calibration parameters for different model responses for minimization of the residual error for different model responses | UBT catchment in Singapore | ACGA is found to be better than SGA, VEGA, MOGA, and NSGA in terms of generating a wider range of solutions in the initial search space, faster convergence rate, and more optimal Pareto front |
| Khu & Madsen (2005) | NSGA-II | Multi-objective calibration with Pareto-preference ordering is generated considering different number and combinations of the objective functions which are minimization of the overall volume error, RMSE, RMSE of peak flow events and RMSE of low flow events | NAM rainfall-runoff model of the Tryggevaelde catchment in Denmark | For highly correlated objective functions, a small number of Pareto-optimal solutions were generated. On comparing the solutions obtained using single-objective optimization, all the solutions were within the bounds of those obtained using single-objective calibration and the spread of the Pareto-optimal set was small, indicating good compromise solutions. The NSGA-II can be used for the calibration of model parameters |
| Zhang et al. (2009) | GA, SCE, PSO, DE and artificial immune system (AIS) | Testing of five optimization algorithms for the automatic parameter calibration of the SWAT model considering maximization of NSE | Yellow River headwaters watershed (YRW), Reynolds Creek Experimental Watershed (RCEW), Little River Experimental Watershed (LREW), and Mahantango Creek Experimental Watershed (MCEW) | No optimization algorithm could perform consistently better than the other algorithms for all four watersheds, implying the complexity of the problem. The study noted that GA could be considered as the first choice for getting global optimum solutions and PSO for getting solutions with lesser computational efforts |
### Table 8 | continued

| Author(s) (year) | Technique used | Work and objectives | Case studies/problems considered | Key findings |
|-----------------|----------------|---------------------|---------------------------------|--------------|
| Zou & Lung (2004) | Alternating Fitness GA (AFGA) | Calibration of water quality models for water quality management using AFGA, which comprises of changing the fitness function evaluations at times throughout the evolution steps for minimization of the sum of squared differences between model generated and observed data | Total phosphorus model of the Triadelphia Reservoir in Maryland | AFGA is capable of generating a higher diversity of solutions compared to the normal GA |
| Tigkas et al. (2016) | SCE, GA, and Evolutionary Annealing-Simplex (EAS) | Comparison of the effectiveness and efficacy of three EAs for automatic calibration of the Medbasin-D Conceptual Hydrological Model for minimization of RMSE, Mean absolute error (MAE), Ratio of mean absolute error to the mean of observed discharge (RMAE), and Maximization of NSE, and Modified NSE (MNSE) | Watershed of the island of Crete in Greece | GA was the most efficient among the three algorithms, while SCE and EAS required a more exhaustive search by reaching the maximum allowed number of functions evaluations in most cases |
| Alamdari et al. (2017) | NSGA-II | Development of an auto-calibration tool to calibrate the Storm Water Management Model (SWMM) and its application for assessing the effects of climate change on water quantity and quality considering maximization of the coefficient of determination (R²) and Nash Sutcliffe Efficiency (NSE), and minimization of Percent Bias (PBIAS) | Difficult Run watershed, Virginia | The model was calibrated and applied successfully to the considered watershed. However, the sources of uncertainty in GCMs were not considered in the study |
| Shin & Choi (2018) | SCE algorithm | Application of combined SCE and hydrologic model for calibration of Grid-based rainfall-runoff model (GRM) for maximization of NSE, maximization of correlation coefficient and minimization of normalized RMSE (nRMSE) | The Danseong and Seonsan catchments, which are major tributary catchments of the Nakdong River in South Korea | The performance of the SCE model was found to be appropriate and can be used for the parameter calibration of other hydrologic models |

(continued)
to changing environments; and the available population of evolved solutions offers a basis for further improvement, and in most cases, it is not needed to reinitialize the population at random. Thus, EAs proved to be effective, especially for problems that are intractable by classic methods of optimization, and for cases where heuristic solutions are not accessible or generally lead to unsatisfactory results.

Table 8 | continued

| Author(s) (year) | Technique used | Work and objectives | Case studies/problems considered | Key findings |
|------------------|----------------|---------------------|---------------------------------|--------------|
| Krishnan et al. (2018) | Shuffled Complex Evolutionary metropolis algorithm (SCEM-UA) | Parameter estimation of SWAT using SCEM-UA considering minimization of RMSE | St. Joseph River basin, USA | The major advantage of the SCEM-UA algorithm is that it helps quantify the uncertainty of the model parameters, along with the calibration process and can achieve the calibration process in less number of function evaluations of the model as compared to other optimization algorithms |
| Mostafaie et al. (2018) | NSGA-II, SPEA, MOPSO, and Pareto Envelope-based Selection Algorithm II (PESA-II) | Comparison of the multi-objective optimization techniques for calibration of GR4 J model (a conceptual hydrologic model) using *in situ* runoff and daily GRACE data for maximization of the NSE for flow and daily total water storage | Danube River Basin, located in the Central and Eastern Europe | NSGA-II produced the best results considering the diversity-based metric, while MOPSO produced better results considering the optimality criteria. All the four algorithms found to perform equally well considering the cardinality (no. of Pareto-optimal solutions obtained) |
| Koppa et al. (2019) | AMALGAM | Application of the DREAM simulation model and AMALGAM optimization model for multi-variate calibration of a large-scale distributed hydrologic model (Noah-MP) for minimization of RMSE for a different combination of model responses: Evapotranspiration (ET), surface moisture (SM) and Streamflow (SF) | Mississippi river basin | The multi-variate calibration process found to be much more efficient than a single variate calibration process |
| Tian et al. (2019) | $\varepsilon$-NSGA-II | Development and use of a single-objective function (i.e., minimization of the summation of a power function of the absolute error between observed and simulated streamflow with the exponent of power function) rather than employing multiple objectives for automatic calibration of hydrologic models | Model Parameter Estimation Experiment (MOPEX) | The single-objective optimization can achieve better hydrographs as compared to traditional NSE efficiency for most watersheds |
Table 9 | Applications of EA and SI meta-heuristic methods for groundwater remediation, groundwater systems, and monitoring network design

| Author(s) (year) | Technique used | Work and objectives | Case studies/problems considered | Key findings |
|------------------|----------------|---------------------|---------------------------------|--------------|
| Dougherty & Marryott (1991) | Simulated Annealing (SA) | Application of SA for application of groundwater management problems considering minimization of cost (cost of well installation, operation, and maintenance, costs associated with water treatment and disposal and costs of failing to achieve specific management goals) | Dewatering problem with zooming and contamination problem | Simulated annealing finds good solutions to problems with highly variable objective functions, whereas gradient methods are very good at finding local solutions for the smooth objective function |
| McKinney & Lin (1994) | GA | Application of GA for maximization of pumping; minimization of cost of water supply; and minimum cost aquifer remediation (solved as three separate problems) | Three hypothetical examples | GA proves to be more efficient than traditional methods like LP, NLP, and DP, especially for complex problems that comprise of discontinuous or highly nonlinear or non-convex problems |
| Ritzel et al. (1994) | GA | Application of GA (and two variants of GA, vector evaluated GA (VEGA) and a Pareto GA) to a multi-objective groundwater pollution contaminant problem considering maximization of reliability (as a fraction of plumes captured) and minimization of system total cost | Hypothetical contamination problem | Pareto GA performs better than VEGA for zero fixed cost solution and obtains a Pareto front similar to that obtained via mixed-integer chance-constrained programming (MICCP) |
| Huang & Mayer (1997) | GA | Dynamic optimization formulation for groundwater remediation using GA considering well locations and pumping rates as the decision variables considering minimization of cost (installation, pumping and treatment cost) | A hypothetical, homogeneous aquifer system and a spatially correlated heterogeneous aquifer system | The moving well location model produced better results as compared to fixed well location models. The model results are found to be more sensitive to well locations rather than the pumping rates. GA found to be an effective technique for solving the GW remediation problem, but more efforts suggested for improving computational efficiency for a larger problem with more number of decision variables |
| Wang & Zheng (1997) | GA | Simulation–optimization model for GW remediation by coupling GA with MODFLOW and MT3D, considering dynamic pumping rates for minimization of the net present value of remedial and operational cost | A hypothetical, homogeneous test problem and a real case study at a site near Granger, Indiana | GA-based method has specific advantages as compared to gradient-based methods such as ease of handling non-linearity, discrete decision variables, able to find optimal (or at least sub-optimal solutions), by considering proper population size and number of iterations |

(continued)
Table 9 | continued

| Author(s) (year)         | Technique used          | Work and objectives                                                                                           | Case studies/problems considered                  | Key findings                                                                                                                                                                                                                                                                                                                                 |
|--------------------------|-------------------------|----------------------------------------------------------------------------------------------------------------|----------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Sun & Zheng (1999)       | GA, DP                  | Dynamic optimization of long-term groundwater management problem (to determine the optimal pumping rates) using DOMODF optimization tool based on differential dynamic programming linked with MODFLOW as the simulation tool for minimization of cost | Two hypothetical problems                          | The combined use of GA (or DDP) and MODFLOW could form an effective tool for solving GW management problems. The method has certain shortcomings as DDP converges only locally while DP converges globally; DDP is also more error sensitive than GA; DOMODF also subjected to the effects of uncertainties in calibrated flow models |
| Smalley et al. (2000)    | Noisy GA                | Risk-based in situ bioremediation design (which considers risks related to human health and the environment associated with a contaminated site) for minimization of the total cost (capital and operating costs for remediation wells, site monitoring costs, additional capital and operating costs associated with remedial systems) | An in situ bioremediation case study and a realistic case study from Borden site | Noisy GA is capable of identifying highly reliable designs from a small number of samples. It can serve as an efficient tool for modeling parameter uncertainty and variability                                                                                             |
| Yoon & Shoemaker (2001)  | Real-coded GA (RGA)     | Application of RGA to bioremediation problem and compared with that of binary-coded GA (BCGA) for minimization of the total pumping cost | Two hypothetical aquifers                           | RGA found to be more computationally efficient and accurate than BCGA                                                                                     |
| Zheng & Wang (2002)      | GA                      | Application of the simulation-optimization (SO) methodology (comprising of MODFLOW as the simulation tool and GA as the optimization tool) on real case study for maximizing Trichloroethylene (TCE) mass removal | Massachusetts Military Reservation (MMR) in the north-eastern United States | The GA-based SO methodology could be successfully applied on desktop PCs. Considerable cost savings can be achieved by adopting dynamic pumping                                                                                                           |
| Erickson et al. (2002)   | Niched Pareto GA (NPGA) | Application of the multi-objective optimization algorithm NPGA for the optimal design of GW remedial systems for minimization of remediation cost and contaminant mass remaining at the end of the remediation horizon | A hypothetical contaminated GW site for two, three and 15 fixed well locations cases | NPGA performed better than SGA and RS, especially in the case of 15 well scenarios requiring 30% less computational efforts as compared to SGA. NPGA lead to better solutions in terms of 75% less remedial contaminant mass                                                                                      |
| Shieh & Peralta (2005)   | Hybrid SA and GA termed as parallel recombinative SA (PRSA) | Application of PRSA for optimizing in situ bioremediation system design considering minimization of total system cost, and minimization of cost of time-varying pumping strategy | Hypothetical study area                             | PRSA minimizes the total system cost better than SA and GA. Optimal time-varying pumping strategy requires 31% less pumping cost than optimal steady pumping strategy                                                                                                         |
| Author(s) (year)     | Technique used | Work and objectives                                                                                                                                                                                                 | Case studies/problems considered                     | Key findings                                                                                                                                                                                                 |
|---------------------|----------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Babbar & Minsker    | Multi-scale GA | Application of multi-scale GA (different than the normal GA in the way it acquires information about the fitness function and the way it manipulates the new individuals) for GW remediation problem with minimization of the total treatment cost | Hypothetical GW remediation problem and a field-scale GW application at Umatilla Chemical Depot in Oregon | The multi-scale GA leads to computational savings of around 77% for a hypothetical case and 78% for the real case study                                                                                      |
| Wu et al. (2006)    | MCSGA and noisy GA | A comparison of Monte Carlo Simulation GA (MCSGA) and Noisy GA (NGA) for the optimal design of sampling network design under uncertainty in hydraulic conductivity for minimization of the total of well installation and sampling cost | A two-dimensional confined aquifer measuring 600 m long in the x-direction and 400 m wide in the y-direction | The solution obtained using NGA leads to 45% cost saving as compared to that obtained using MCSGA. Compared to MCSGA, NGA reduces the optimization runtime by a factor of 6.5                                                                 |
| Park et al. (2007)  | GA             | Development of an Enhanced natural attenuation (ENA) optimization process for optimal GW remediation design for minimization of the remediation cost                                                                 | A hypothetical 2D unconfined aquifer                | The ENA process led to improved efficiency of the remediation strategy                                                                                                                                       |
| Mantoglou & Kourakos (2007) | MOGA | Development of a methodology for optimal remediation of GW aquifers under hydraulic conductivity uncertainty for minimization of contaminated groundwater in the aquifer and minimization of remediation cost | A hypothetical orthogonal unconfined aquifer       | The MOGA has produced good results. In the example considered, only 11 realizations out of 100 were found to be critical, implying 89% saving in computational time                                                                 |
| Tang et al. (2007)  | ε-NSGA-II      | Demonstration and evaluation of the Master-Slave (MS) and Multiple-Population (MP) parallelization schemes for NSGA-II considering minimization of the monitoring cost (for GW monitoring application) | DTLZ optimization function, hydrologic model calibration test case for the Leaf River near Collins, Mississippi, and a GW monitoring application | The ε-NSGA-II method found to be generating good Pareto-optimal solutions. Multi-population was found to be superior to the Master-slave scheme only for the DTLZ optimization problem, while for other problems, MS is found to perform better than MP                                                                                     |
| Chadalavada & Datta (2008) | GA            | Development of a model for optimal GW pollution monitoring network design to determine the optimal and efficient sampling locations for detecting pollution in GW aquifers considering minimization of the summation of unmonitored concentrations at different potential monitoring locations; and minimization of estimation variances of pollutant concentrations at various unmonitored locations | An illustrative study area comprising of a hypothetical aquifer | The designed network of optimal monitoring wells is dynamic in nature, which results in economically efficient designs. However, the stochastic nature of the processes involved has not been explicitly incorporated into the model                                                                 |
| Author(s) (year)          | Technique used | Work and objectives                                                                                                                                                                                                                                                                                                                                 | Case studies/problems considered                                                                                                                                  | Key findings                                                                                                                                                          |
|--------------------------|----------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Kobayashi et al. (2008)  | SA             | Development of a SA based SO model for multiphase/multicomponent flow simulation, by incorporating a parallelization procedure for the optimization model considering maximization of the amount of methane extracted from the wells | A two-phase (liquid, gas)/three-component (water, methane, air) conceptual model, and a coal mining site in the Ruhr, Germany                                         | The SA based methodology and parallelization scheme enhanced the computational efficiency of the overall procedure almost linearly by the number of processors in the parallel computer |
| Bayer et al. (2008)      | GA             | Development of a computationally efficient method for stochastic optimization problems which involves multiple equally probable realisations of the uncertain parameters for maximization of the pumping rates of all wells | A synthetic groundwater model set-up                                                                                                                                                                                                 | The computational efficiency is improved manifolds by applying the stack ordering procedure. In the case of more advanced stack ordering strategies, almost 97% of the computational efficiency can be achieved. The presented approach is also independent of the problem to be solved |
| Singh et al. (2008)      | Interactive MOGA (IMOGA) | Development of an interactive multi-objective model for groundwater inverse modeling for estimating heterogeneous GW parameters for minimization of the calibration error with respect to field measurements, and a qualitative objective that reflects an expert’s qualitative preferences | A hypothetical aquifer case study consisting of six pumping wells and 16 observation wells                                                                          | The results obtained without considering the quantitative preferences lead to sub-optimal solutions. IMOGA found to be an efficient tool for incorporating expert knowledge into the multi-objective formulation |
| Singh & Chakrabarty (2011) | NSGA-II      | Application of NSGA-II to solve GW remediation problem considering minimization of remediation cost and minimization of remediation time                                                                                                                                                                                                                     | A hypothetical confined multi-layered aquifer                                                                                                                                                                                  | The NSGA-II generated a good number of Pareto-optimal solutions; and noted that remediation time plays a crucial role in the optimal design of GW remedial systems |
| Luo et al. (2016)        | Probabilistic Pareto GA (PPGA) | Optimal design of long-term groundwater monitoring network (LTGM), considering the uncertainty in K-fields for minimization of (i) the total sampling costs for monitoring contaminant plume, (ii) mass estimation error, (iii) the first-moment estimation error, and (iv) the second-moment estimation error of the contaminant plume | A two-dimensional hypothetical example and a three-dimensional field application in Indiana (USA)                                                                                                                                  | The optimization results show the high accuracy of the PPGA. However, the computational burden was extensively large when considering the uncertainties |
| Ouyang et al. (2017)     | AMALGAM        | Application of AMALGAM for GW remediation design and comparison with NSGA-II for minimization of the total remediation cost, and minimization of the remediation time                                                                                                                                                                                                 | A hypothetical perchloroethylene (PCE) contaminated site                                                                                                                                                                          | The AMALGAM results incurred less remediation cost and required less computational time as compared to NSGA-II |

(continued)
Which evolutionary algorithm to use?

There were several variants of EAs. Each of the meta-heuristic algorithms has its own advantages and disadvantages. Among the nature-inspired EAs, GA is one of the oldest and popular techniques that has several applications in the water resources field. The main advantages include its ability to handle nonlinear, nonconvex, nondifferentiable functions, multi-modal solutions and can provide optimal or near-optimal solutions to a given problem. Real-coded GA has advantages over binary-coded GA for real-valued decision variable problems. However, GA requires the selection of appropriate genetic operators among several versions available and proper tuning of the parameters such as probabilities of crossover and mutation, population size, etc. Also, the optimization process may take higher computational time for complex water resources problems such as groundwater systems monitoring and remediation, WDN problems, etc., as it may involve a time-consuming simulation–optimization process. The other popular algorithm, differential evolution, also has advantages similar to that of GA; apart from that, it is proved that DE has faster convergence and reliable, optimal solutions for numerical optimization. DE also has limitations in selecting an appropriate version of DE and algorithm parameters. Similarly, other EAs (like SCE, ES) are found to have similar capabilities and difficulties while solving water resources optimization problems. A brief summary of the comparison of basic characteristics and quality performance features of different EA (GA, DE, ES) are given in Table 10. However, the recent developments of self-adaptive EAs (e.g., SADE) are found to be overcoming this issue and helping the tuning of the algorithm parameters as the search progresses.
Which SI algorithm to use?

Several variants of the SI algorithms (like PSO, ACO, ABC, HBMO, FFA, BA, etc.) were proposed in different studies. The SI methods are basically inspired by co-operative group intelligence principles of the swarm and proved to be other classes of alternative meta-heuristic techniques for solving different kinds of optimization problems in water resources. Similar to EAs, SI algorithms are population-based random search techniques guided with some heuristics, which can also handle different types of problem complexities (like nonlinear, nonconvex, nondifferentiable functions, multi-modal solutions, etc.). But their applicability and convergence characteristics may vary from problem to problem. For example, PSO is a technique applicable for real-valued decision variables, has advantages of easiness in coding the algorithm, provides fast convergence to simple numerical problems, and requires low computational time. However, fine-tuning of algorithm parameters (e.g., inertia weight, social, and cognitive parameters) is required for getting optimal solutions and consistently good performance from the method. But, the basic PSO may face difficulties like premature convergence to locally optimal solutions for higher dimensional, large-scale water
resources problems. Several studies proposed different strategies for the improvement of the PSO performance (like EMPSO proposed by Kumar & Reddy 2007). The ACO method is also a random search method guided by probabilistic rules and some heuristics (i.e., pheromone laying behavior of ants) and can produce global-optimal solutions. But ACO is applicable effectively only for a set of problems that involve decision variables with discrete values (for example, the WDNs problem can be represented in graphical form/shortest path that can be easily covered by the ants, and it can be modeled with pheromone trail laying behavior). There are several variants of ACO algorithms. It has similar advantages to other EAs in handling different kinds of complexities. However, the performance of ACO is sensitive to its algorithmic parameters, so it may require tuning of the parameters such as relative pheromone trail, heuristic information, evaporation rate, etc. while solving large-scale problems. Other SI algorithms (like ABC, HBMO, CS, FFA, BA algorithms) also have similar capabilities and limitations like that of PSO. A brief summary of basic characteristics and quality performance features a comparison of different EAs (PSO, ACO, and ABC) that are presented in Table 10.

It should also be noted that different studies have presented different algorithms for solving water problems and noted that some algorithms are relatively better than other methods. But, the inferences made may be applicable for those problems, which may not be generalized to one or not applicable for all types of problems, as each problem may have varying complexity depending on the dimension of the problem and existing relationships for the problem in hand. So, proper selection and usage of the algorithm for a given problem should be based on the problem type and its characteristics.

Hybrid meta-heuristic methods?

Research studies also reported that hybrid meta-heuristic methods that combine global-search with local search algorithms found to be providing improved performance for large-scale water resources optimization problems. Also, several strategies like problem-specific heuristics, chaotic concepts into the initialization of population, elitism concepts, self-adaptive schemes, etc., are incorporated into SI algorithms to improve the performance of the existing methods and to get consistent satisfactory results. Also, to handle the issues related to multi-objective optimization, different studies have suggested different schemes for getting an array of uniform widespread and true Pareto-optimal solutions for different kinds of practical problems.

FUTURE WORK AND RESEARCH DIRECTIONS

There are several issues which require more research efforts to improve the solutions to the practical problems in the water resources engineering area. Some of these issues and future research directions are listed below.

Improvement in algorithm and solution methodology

There is a great deal of research on-going on the development of the new algorithms, a better understanding of the algorithm’s performance and search behavior, analyzing the suitability in handling the different complexities of the problems, etc. As the meta-heuristic methods are population-based search algorithms and involve several parameters (like population size, maximum generations/iterations, other algorithm-specific parameters) to start the optimization procedure, and also the model performance is sensitive to the selected parameters. This warrants for proper fine-tuning of parameters before applying to a given problem. To address this issue of how to overcome the effect of
the sensitivity of the parameters on the performance of the algorithm, recently, several studies explored self-adaptive schemes for overcoming this issue. For improving computational efficiency, studies also explored guided initialization of population, parallelization schemes (parallel processing that uses two more CPUs for computations saves time, which is well suited for population-based EA/SI methods that use simulation-optimization framework for solving complex real-world problems), the multi-algorithm search that combines two or more (global and/or local) search algorithms, etc. But still, there is a scope for improvements and more research is needed in this area. Moreover, it is important to develop knowledge related to the suitability of various optimization methods for a particular type of water resource problem and the incorporation of domain knowledge in the search, which can also help in improved solution methodology.

**Search space reduction and improving computational efficiency**

The complexity of the real-world problems (especially for problems in the areas of water distribution systems, groundwater systems management, calibration of distributed hydrological models) is increasing day-by-day, and it is expected to continue critical and promising research areas in the future also. Recently several studies are focusing on the issues of how to reduce the search space and guide the algorithms to speed up the convergence and/or improve the reliability in achieving global-optimal solutions. Schemes like fitness approximation, parallelization, and multi-algorithm search frameworks have been explored. But, still much more research is needed to come up with better strategies.

**Model inputs and uncertainty**

Since the model inputs may involve different kinds of uncertainty, there is a necessity to explore how to best represent various types of uncertainties (such as aleatoric and epistemic uncertainty) in the optimization model and incorporate them into decision making. Also, future uncertainties due to climate change, urbanization, etc., might affect the planning of water resources systems, and exploring new frameworks and evolving flexible design is one of the promising areas for future research.

**Solution post-processing and decision making**

The solutions obtained by solving an optimization model are sensitive to a given input variables condition. This poses doubts of how reliable are the solutions, considering the changing conditions or input variable values. In the case of multi-objective optimization (with more than two objectives), the MOEAs generate a large number of Pareto-optimal solutions. Then the challenge is how to use them for decision making, as it is difficult to visualize and choose the solutions. So, more efforts are needed to come up with effective decision-making procedures, which can help and equip the users in envisaging the trade-offs and assist in arriving at few practical alternatives and/or facilitate effective decision making under several conflicting goals.

**CONCLUDING REMARKS**

Real-life water resource planning and management problems may involve several complexities and may pose several challenges for decision-makers. The use of evolutionary algorithms for solving numerical and practical optimization problems has become very attractive and extensive in the last three decades. Several new meta-heuristic algorithms including EA (such as GA, DE, SCE, etc.) and SI algorithms (such as PSO, ACO, ABC, SFL, HBMO, HS, FFA, CS, BA, etc.) are being proposed, which showed improved performance for solving a variety of water resources problems. The main advantage of EAs is the usage of a population of potential solutions that explore the search space.
simultaneously, exchanging information among them, and uses only objective function values. Also, EAs are stochastic search algorithms, can move to any complicated search space and locate near-optimal (or optimal) solutions in reasonable computational time. They can provide solutions to any complex optimization problem that is difficult to be solved with the conventional NLP methods due to their nature that may imply discontinuities of the search space, nondifferentiable objective functions, imprecise arguments and function values.

Some of the remarks on the current state-of-the-art in EAs:

- There is no general algorithm that can be applied efficiently to all problems, as the efficiency varies as a function of problem size and complexity. However, the incorporation of problem-specific knowledge and heuristics may help to achieve faster and efficient solutions to a real-world problem.
- EAs may require calibration of the search parameters to ensure efficient convergence. The self-adaptive EA as part of improving the solution methodology can help to arrive quickly at near-optimal (or optimal) solutions, thereby helping water resources engineers in a better decision-making process.
- For complex problems, EAs may require a large number of simulations to find optimal solutions. In such cases, the use of meta-modeling, fitness approximation, parallelization schemes may help to speed up the simulation—optimization process, thereby helping in improving computational efficiency.
- The different types of problem complexities and their associated uncertainties motivate a great need for advances in multi-objective search, interactive optimization, and multi-algorithm search frameworks.

Therefore, EAs continue growing interest among the research community, and there is a tremendous potential for solving many practical water resources problems.

ACKNOWLEDGEMENTS

Authors acknowledge Ms Swati Sirsant (Civil Engineering, IIT Bombay) for assistance in compiling some of the literature used in the study.

REFERENCES

Abbass, H. A. 2001 Marriage in honey bees optimisation: a haplometrosis polygynous swarming approach. In: Congress on Evolutionary Computation, CEC2001. Vol. 1. Seoul, Korea, pp. 207–214.
Afshar, M. H., Afshar, A., Marino, M. A. & Darbandi, A. A. 2006 Hydrograph-based storm sewer design optimization by genetic algorithm. Canadian Journal of Civil Engineering 33 (5), 319–325.
Ahram, A., Deb, K. & Preuss, M. 2017 Multimodal optimization by covariance matrix self-adaptation evolution strategy with repelling subpopulations. Evolutionary Computation 25 (3), 459–471.
Akimoto, Y., Auger, A. & Hansen, N. 2018 Quality gain analysis of the weighted recombination evolution strategy on general con- vex quadratic functions. Theoretical Computer Science. https://doi.org/10.1016/j.tcs.2018.05.015.
Alamdar, N., Sample, D. J., Steinberg, P., Ross, A. C. & Easton, Z. C. 2017 Assessing the effects of climate change on water quantity and quality in an urban watershed using a calibrated stormwater model. Water 9 (7), 464.
Ali, W. M. 2014 RDEL: Restart differential evolution algorithm with local search mutation for global numerical optimization. Egyptian Informatics Journal 15 (3), 175–188.
Alizadeh, Z., Yazdi, J. & Moridi, A. 2018 Development of an entropy method for groundwater quality monitoring network design. Environmental Processes 5 (4), 769–788.
Aminjavaheri, S. M. & Nazif, S. 2018 Determining the robust optimal set of BMPs for urban runoff management in data-poor catchments. Journal of Environmental Planning and Management 61 (7), 1180–1203.
Arnold, D. V. 2006 Weighted multi recombination evolution strategies. Theoretical Computer Science 361 (1), 18–37.
Artita, K. S., Kaini, P. & Nicklow, J. W. 2013 Examining the possibilities: generating alternative watershed-scale BMP designs with evolutionary algorithms. Water Resources Management 27 (11), 3849–3863.
Babbar, M. & Minsker, B. S. 2006 Groundwater remediation design using multiscale genetic algorithms. Journal of Water Resources Planning and Management 132 (5), 341–350.
Barreto, W. J., Vojinovic, Z., Price, R. K. & Solomatine, D. P. 2006 Approaches to multi-objective multi-tier optimization in urban drainage planning. In: 7th International Conference Proceedings on Hydroinformatics, HIC, Nice, France, pp. 1–8.

Barreto, W., Vojinovic, Z., Price, R. & Solomatine, D. 2010 Multiobjective evolutionary approach to rehabilitation of urban drainage systems. *Journal of Water Resources Planning and Management* 136 (5), 547–554.

Bayer, P., Bürger, C. M. & Finkel, M. 2008 Computationally efficient stochastic optimization using multiple realizations. *Advances in Water Resources* 31 (2), 399–417.

Bellman, R. E. 1957 *Dynamic Programming*. Princeton University Press, Princeton, New Jersey.

Beyer, H. G. & Sendhoff, B. 2017 Simplify your covariance matrix adaptation evolution strategy. *IEEE Transaction on Evolutionary Computation* 21 (5), 746–759.

Bhushan, B. & Pillai, S. S. 2013 Particle swarm optimization and firefly algorithm: performance analysis. In: 3rd *IEEE International Advance Computing Conference*. IEEE, Ghaziabad.

Blum, C. 2008 Beam-ACO for simple assembly line balancing. *INFORMS Journal on Computing* 20 (4), 618–627.

Bonabeau, E., Dorigo, M. & Theraulaz, G. 1999 *Swarm Intelligence: From Natural to Artificial Systems*. Oxford University Press, New York, NY.

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 (6), 646–657.

Brest, J., Zamuda, A., Fister, I. & Boskovic, B. 2014 Some improvements of the self-adaptive jDE algorithm. In: *IEEE Symposium on Differential Evolution (SDE)*. pp. 1–8.

Brownlee, J. 2011 *Clever Algorithms: Nature-Inspired Programming Recipes*. LuLu.com, Australia.

Chadalavada, S. & Datta, B. 2008 Dynamic optimal monitoring network design for transient transport of pollutants in groundwater aquifers. *Water Resources Management* 22 (6), 651–670.

Chen, S.-M. & Chien, C.-Y. 2011 Solving the traveling salesman problem based on the genetic simulated annealing ant colony system with particle swarm optimization techniques. *Expert Systems with Applications* 38 (12), 14439–14450.

Chen, W. C., Chang, N. B. & Chen, J. C. 2003 Rough set-based hybrid fuzzy-neural controller design for industrial wastewater treatment. *Water Research* 37 (1), 95–107.

Chen, H., Zhu, Y. & Hu, K. 2010 Multi-colony bacteria foraging optimization with cell-to-cell communication for RFID network planning. *Applied Soft Computing* 10, 539–547.

Cheung, P. B., Reis, L. F. R., Formiga, K. T. M., Chaudhry, F. H. & Ticona, W. G. C. 2003 Multiobjective evolutionary algorithms applied to the rehabilitation of a water distribution system: a comparative study. In: *International Conference on Evolutionary Multi-Criterion Optimization*. Springer, Berlin, Heidelberg, pp. 662–676.

Choi, T. J. & Ahn, C. W. J. 2014 An adaptive cauchy differential evolution algorithm with bias strategy adaptation mechanism for global numerical optimization. *Journal of Computers* 9 (8), 2139–2145.

Choi, T. J., Ahn, C. W. & An, J. 2013 An adaptive Cauchy differential evolution algorithm for global numerical optimization. *Scientific World Journal* 2013, 12. article ID: 969734.

Chung, G. & Lansey, K. 2009 Application of the shuffled frog leaping algorithm for the optimization of a general large-scale water supply system. *Water Resources Management* 23 (4), 797.

Clerc, M. 1999 The swarm and the queen: towards a deterministic and adaptive particle swarm optimization. In: *IEEE Congress on Evolutionary Computation*. pp. 1951–1957.

Clerc, M. 2004 *Discrete Particle Swarm Optimization, Illustrated by the Traveling Salesman Problem, New Optimization Techniques in Engineering*. Springer, pp. 219–239.

Creaco, E., Fortunato, A., Franchini, M. & Mazzola, M. R. 2014 Comparison between entropy and resilience as indirect measures of reliability in the framework of water distribution network design. *Procedia Engineering* 70, 379–388.

Cunha, M. & Ribeiro, L. 2004 Tabu search algorithms for water network optimization. *European Journal of Operational Research* 157 (3), 746–758.

Dandy, G. C. & Engelhardt, M. 2001 Optimal scheduling of water pipe replacement using genetic algorithms. *Journal of Water Resources Planning and Management* 127 (4), 214–223.

Dandy, G. C. & Engelhardt, M. O. 2006 Multi-objective trade-offs between cost and reliability in the replacement of water mains. *Journal of Water Resources Planning and Management* 132 (2), 79–88.

Das, S., Mullick, S. S. & Suganthan, P. N. 2016 Recent advances in differential evolution – an updated survey. *Swarm and Evolutionary Computation* 27, 1–30.

Deb, K. & Jain, H. 2014 An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints. *IEEE Transactions on Evolutionary Computation* 18 (4), 577–601.

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

DeLevaQue, A., Delisle, P., Gravel, M. & Krajecki, M. 2013 Parallel ant colony optimization on graphics processing units. *Journal of Parallel and Distributed Computing* 73 (1), 52–61.

Dessalegne, T., Nicklow, J. & Minder, E. 2004 Evolutionary computation to control unnatural water level fluctuations in multi-reservoir river systems. *River Research and Applications* 20 (6), 619–634.

Di Caro, G. & Dorigo, M. 1998 AntNET: distributed stigmergetic control for communications networks. *Journal of Artificial Intelligence Research* 9 (9), 317–365.
Dorigo, M. & Gambardella, L. M. 1997 Ant colony system: a cooperative learning approach to the traveling salesman problem. IEEE Transactions on Evolutionary Computation 1 (1), 55–66.

Dorigo, M. & Stutzle, T. 2004 Ant Colony Optimization. MIT Press, Cambridge, Massachusetts.

Dorigo, M., Maniezzo, V. & Colomi, A. 1991 Positive Feedback as A Search Strategy. Technical Report 91-016. Politecnico di Milano, Italy.

Dorigo, M., Maniezzo, V. & Colomi, A. 1996 Ant system: optimization by a colony of cooperating agents. IEEE Transactions on Systems, Man, and Cybernetics, Part B 26 (1), 29–41.

Dougherty, D. E. & Marroyo, R. A. 1991 Optimal groundwater management: 1. Simulated annealing. Water Resources Research 27 (10), 2493–2508.

Draa, A., Chetliah, K. & Talbi, H. 2019 A compound sinusoidal differential evolution algorithm for continuous optimization. Swarm and Evolutionary Computation 50, 100450.

Eberhart, R. C. & Kennedy, J. 1995 A New optimizer using particle swarm theory. In: Proceedings of 6th Symposium on Micro Machine & Human Science. IEEE Service Center, Piscataway, New Jersey, pp. 39–43.

Elloumi, W., Baklouti, N., Abraham, A. & Alimi, A. M. 2014 The multi-objective hybridization of particle swarm optimization and fuzzy ant colony optimization. Journal of Intelligent and Fuzzy Systems 27 (1), 515–525.

Ericsson, M., Mayer, A. & Horn, J. 2002 Multi-objective optimal design of groundwater remediation systems: application of the niched Pareto genetic algorithm (NPGA). Advances in Water Resources 25 (1), 51–65.

Eusuff, M. M. & Lansey, K. E. 2003 Optimization of water distribution network design using the shuffled frog leaping algorithm. Journal of Water Resources Planning and Management 129 (3), 210–225.

Falkenauer, E. 1996 The grouping genetic algorithm. In: State of the Art in Global Optimization. pp. 249–265.

Fallah, H., Ghazanfari, S., Suribabu, C. R. & Rashedi, E. 2019 Optimal pipe dimensioning in water distribution networks using Gravitational Search Algorithm. ISH Journal of Hydraulic Engineering 1–14. https://doi.org/10.1080/09715010.2019.1624630.

Farmani, R., Savic, D. A. & Walters, G. A. 2005 Evolutionary multi-objective optimization in water distribution network design. Engineering Optimization 37 (2), 167–183.

Fogel, D. B. 1994 An introduction to simulated evolutionary optimization. IEEE Transactions on Neural Networks 5 (1), 3–14.

Fogel, L. J., Owens, A. J. & Walsh, M. J. 1966 Artificial Intelligence Through Simulated Evolution. Wiley, New York.

Franchini, M. & Galeati, G. 1997 Comparing several genetic algorithm schemes for the calibration of conceptual rainfall-runoff models. Hydrological Sciences Journal 42 (3), 357–379.

Fu, G., Butler, D. & Khu, S. T. 2008 Multiple objective optimal control of integrated urban wastewater systems. Environmental Modelling and Software 25 (2), 225–234.

Gambardella, L. M., Taillard, E. & Agazzi, G. 1999 MACS-VRPTW: a multiple ant colony system for vehicle routing problems with time windows. In: New Ideas in Optimisation (Corne, D., Dorigo, M. & Glover, F., eds). McGraw-Hill, London, UK, pp. 63–76.

Geem, Z. W. 2006 Optimal cost design of water distribution networks using harmony search. Engineering Optimization 38 (03), 259–277.

Geem, Z. W., Kim, J. H. & Loganathan, G. V. 2001 A new heuristic optimization algorithm: harmony search. Simulation 76 (2), 60–68.

Gessler, J. 1985 Pipe network optimization by enumeration. In: Computer Applications in Water Resources. ASCE, pp. 572–581.

Ghasemi, M., Taghizadeh, M., Ghavidel, S. & Abbasi, A. 2016 Colonial competitive differential evolution: an experimental study for optimal economic load dispatch. Applied Soft Computing 40, 342–363.

Ghimire, B. N. S. & Reddy, M. J. 2013 Optimal reservoir operation for hydropower production using particle swarm optimization and sustainable analysis of hydropower. ISH Journal of Hydrological Engineering 19 (3), 196–210.

Glasmachers, T., Schaul, T., Sun, Y., Wierstra, D. & Schmidhuber, J. 2010 Exponential natural evolution strategies. In: Proceedings of the Genetic and Evolutionary Computation Conference. GECCO’10, Portland, Oregon, USA, pp. 593–400. https://doi.org/10.1145/1830483.1830557.

Goh, C. K., Tan, K. C., Liu, D. & Chiam, S. C. 2010 A competitive and cooperative co-evolutionary approach to multi-objective particle swarm optimization algorithm design. European Journal of Operations Research 202, 42–54.

Goldberg, D. E. 1989 Genetic Algorithms in Search, Optimization and Machine Learning, 1st edn. Addison-Wesley Longman Publishing Co., Toronto, Ontario, Canada.

Gunstch, M. & Middendorf, M. 2002 A population based approach for ACO. In: Workshops on Applications of Evolutionary Computation. Springer, pp. 72–81.

Guo, Y., Walters, G. A., Khu, S. T. & Keedwell, E. 2006 Optimal design of sewer networks using hybrid cellular automata and genetic algorithm. In: Proceedings of the 5th IWA WorldWater Congress, London. IWA Publishing, London.

Guria, C., Bhattacharya, P. K. & Gupta, S. K. 2005 Multi-objective optimization of reverse osmosis desalination units using different adaptations of the non-dominated sorting genetic algorithm (NSGA). Computers and Chemical Engineering 29 (9), 1977–1995.

Halhal, D., Walters, G. A., Ouazar, D. & Savic, D. A. 1997 Multiobjective improvement of water distribution systems using a structured messy genetic algorithm approach. Journal of Water Resources Planning and Management ASCE 125 (3), 137–146.

Hang, N. T. T. & Chikamori, H. 2017 Comparison of efficiency between differential evolution and evolution strategy: application of the LST model to the Be River catchment in Vietnam. Paddy and Water Environment 15, 797–808.
Harik, G. R. 1997 Learning Gene Linkage to Efficiently Solve Problems of Bounded Difficulty Using Genetic Algorithms. PhD Thesis, University of Michigan, Ann Arbor, MI.

Harrell, L. J. & Ranjithan, S. R. 2003 Detention pond design and land use planning for watershed management. Journal of Water Resources Planning and Management 129 (2), 98–106.

He, Y. & Hui, C.-W. 2006 Dynamic rule-based genetic algorithm for large-size single-stage batch scheduling. Comput-Aided Chemical Engineering 21, 1911–1916.

Holland, J. H. 1975 Adaptation in Natural and Artificial Systems. University of Michigan Press, Ann Arbor, Michigan.

Huang, C. & Mayer, A. S. 1997 Pump-and-treat optimization using well locations and pumping rates as decision variables. Water Resources Research 33 (5), 1001–1012.

Huang, C.-L., Huang, W.-C., Chang, H.-Y., Yeh, Y.-C. & Tsai, C.-Y. 2013 Hybridization strategies for continuous ant colony optimization and particle swarm optimization applied to data clustering. Applied Soft Computing Journal 13 (9), 3864–3872.

Iredi, S., Merkle, D. & Middendorf, M. 2001 Bi-criterion optimization with multi colony ant algorithms. In: Evolutionary Multi-Criterion Optimization, First International Conference (EMO’01). Springer Verlag, Zurich, pp. 359–372.

Jafari-Marandi, R. & Smith, B. K. 2017 Fluid genetic algorithm (FGA). Journal of Computational Design and Engineering 4, 158–167.

Janson, S., Alba, E., Derrac, J. & Middendorf, M. 2006 Hierarchical cellular genetic algorithm. In: Proceedings of the European Conference on Evolutionary Computation in Combinatorial Optimization. EvoCOP. Lecture Notes in Computer Science. Springer, Berlin, Heidelberg, Vol. 3906, pp. 111–122. https://doi.org/10.1007/11730095.

Jayaram, N. & Srinivasan, K. 2008 Performance-based optimal design and rehabilitation of water distribution networks using life cycle costing. Water Resources Research 44 (1), W01417, 1–15. https://doi.org/10.1029/2006WR005316.

Jung, J. J., Jo, G.-S. & Yeo, S.-W. 2007 Meta-evolution strategy to focused crawling on semantic web. In: International Conference on Artificial Neural Networks, ICANN 2007. Lecture Notes in Computer Science, Vol. 4669. Springer, Berlin, Heidelberg, pp. 399–407.

Kadu, M. S., Gupta, R. & Bhave, P. R. 2008 Optimal design of water networks using a modified genetic algorithm with reduction in search space. Journal of Water Resources Planning and Management 134 (2), 147–160.

Kapelan, Z. S., Savic, D. A. & Walters, G. A. 2005 Multiobjective design of water distribution systems under uncertainty. Water Resources Research 41 (11), W1407, 1–15. https://doi.org/10.1029/2004WR003787.

Karaboga, D. 2005 An Idea Based on Honey Bee Swarm for Numerical Optimization. Technical Report-TR06. Erciyes University, Turkey.

Karamouz, M. & Nazif, S. 2013 Reliability-based flood management in urban watersheds considering climate change impacts. Journal of Water Resources Planning and Management 139 (5), 520–533.

Karovic, O. & Mays, L. W. 2014 Sewer system design using simulated annealing in excel. Water Resources Management 28 (13), 4551–4565.

Keedwell, E. & Ku, S. T. 2005 A hybrid genetic algorithm for the design of water distribution networks. Engineering Applications of Artificial Intelligence 18 (4), 461–472.

Kennedy, J., Eberhart, R. C. & Shi, Y. 2001 Swarm Intelligence. Morgan Kaufmann, San Francisco.

Keraichick, R. & Karamouz, M. 2006 Optimal reservoir operation considering the water quality issues: a stochastic conflict resolution approach. Water Resources Research 42 (12), W12401, 1–17. https://doi.org/10.1029/2005WR004575.

Keraichick, R. & Karamouz, M. 2007 A stochastic conflict resolution model for water quality management in reservoir–river systems. Advances in Water Resources 30 (4), 866–882.

Khu, S. T. & Madsen, H. 2005 Multiobjective calibration with Pareto preference ordering: an application to rainfall-runoff model calibration. Water Resources Research 41 (3), W03004, 1–14. https://doi.org/10.1029/2004WR003041.

Kiranyaz, S., Pulkkinen, J. & Gabbouj, M. 2011 Multi-dimensional particle swarm optimization in dynamic environments. Expert Systems with Applications 38 (3), 2212–2223. https://doi.org/10.1016/j.eswa.2010.08.009.

Kobayashi, K., Hinkelmann, R. & Helmig, R. 2008 Development of a simulation-optimization model for multiphase systems in the subsurface: a challenge to real-world simulation-optimization. Journal of Hydroinformatics 10 (2), 139–152.

Koppa, A., Gebremichael, M. & Yeh, W. W. 2019 Multivariate calibration of large scale hydrologic models: the necessity and value of a Pareto optimal approach. Advances in Water Resources 130, 129–146.

Krishnakumar, K. 1990 Micro-genetic algorithms for stationary and non-stationary function optimization. In: Proceedings: Intelligent Control and Adaptive Systems. SPIE, Vol. 1196, pp. 289–296. https://doi.org/10.1117/12.969927.

Krishnan, N., Raj, C., Chaubey, I. & Sudheer, K. P. 2018 Parameter estimation of SWAT and quantification of consequent confidence bands of model simulations. Environmental Earth Sciences 77 (12), 470.

Krishnanand, K. N. & Ghose, D. 2006 Glowworm swarm based optimization algorithm for multimodal functions with collective robotics applications. Multiagent and Grid Systems 2 (3), 209–222. DOI: 10.3233/MGS-2006-2301.

Kumar, D. N. & Reddy, M. J. 2006 Ant colony optimization for multipurpose reservoir operation. Water Resources Management 20 (6), 879–898.

Kumar, D. N. & Reddy, M. J. 2007 Multipurpose reservoir operation using particle swarm optimization. Journal of Water Resources Planning and Management 133 (3), 192–201.
Kumar, D. N., Raju, K. S. & Ashok, B. 2006 Optimal reservoir operation for irrigation of multiple crops using genetic algorithms. *Journal of Irrigation and Drainage Engineering* 132 (2), 125–129.

Kuo, J. T., Wang, Y. Y. & Lung, W. S. 2006 A hybrid neural-genetic algorithm for reservoir water quality management. *Water Research* 40 (7), 1367–1376.

Larvic, V., Iancu, P. & Plešu, V. 2005 Genetic algorithm optimisation of water consumption and wastewater network topology. *Journal of Cleaner Production* 15 (15), 1405–1415.

Lee, J. G., Selvakumar, A., Alvi, K., Riverson, J., Zhen, J. X., Shoemaker, L. & Lai, F. H. 2012. A watershed-scale design optimization model for stormwater best management practices. *Environmental Modelling and Software* 37, 6–18.

Lerma, N., Paredes-Arquiola, J., Andreu, J., Solera, A. & Sechi, G. M. 2015 Assessment of evolutionary algorithms for optimal operating rules design in real Water Resource Systems. *Environmental Modelling and Software* 69, 425–436.

Li, M., Lin, D. & Kuo, J. 2012 A hybrid niching PSO enhanced with recombination-replacement crowding strategy for multimodal function optimization. *Applied Soft Computing* 12, 975–987.

Liang, L. Y., Thompson, R. G. & Young, D. M. 2004 Optimising the design of sewer networks using genetic algorithms and Tabu search. *Engineering, Construction, and Architectural Management* 11 (2), 101–112. https://doi.org/10.1108/0969980410527849.

Liaw, R. T. & Ting, C. K. 2016 Enhancing covariance matrix adaptation evolution strategy through fitness inheritance. In: *Proceedings of the IEEE Congress on Evolutionary Computation (CEC)*. Vancouver, BC, pp. 1956–1963.

Liong, S. Y., Khu, S. T. & Chan, W. T. 2001 Derivation of Pareto front with genetic algorithm and neural network. *Journal of Hydrologic Engineering* 6 (1), 52–61.

Loschilov, I. 2014 A computationally efficient limited memory CMA-ES for large scale optimization. In: *Proceedings of the Genetic and Evolutionary Computation Conference, GECCO*, pp. 397–404.

Luo, Q., Wu, J., Yang, Y., Qian, J. & Wu, J. 2016 Multi-objective optimization of long-term groundwater monitoring network design using a probabilistic Pareto genetic algorithm under uncertainty. *Journal of Hydrology* 534, 352–363.

Ma, B. & Xia, Y. 2017 A tribe competition-based genetic algorithm for feature selection in pattern classification. *Applied Soft Computing* 58, 328–338.

Mackie, G., Savic, G. A. & Walters, G. A. 1995 Application of genetic algorithms to pump scheduling for water supply. In: *First International Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications*. IET, Sheffield, pp. 400–405.

Maier, H. R., Simpson, A. R., Zecchin, A. C., Maier, H. R., Simpson, A. R., Zecchin, A. C., Foong, W. K., Phang, K. W., Seah, H. Y. & Tan, C. L. 2003 Ant colony optimization for the design of water distribution systems. *Journal of Water Resources Planning and Management* 129 (3), 200–209.

Maier, H. R., Kapelan, Z. & Marchi, A. 2014 Evolutionary algorithms and other metaheuristics in water resources: current status, research challenges, and future directions. *Environmental Modelling and Software* 62 (2014), 271–299.

Mallipeddi, R., Suganthan, P. N., Pan, Q. K. & Tasgetiren, M. F. 2011 Differential evolution algorithm with ensemble of parameters and mutation strategies. *Applied Soft Computing* 11 (2), 1679–1696.

Man, K. F., Chan, T. M., Tang, K. S. & Kwong, S. 2004 Jumping-genes in evolutionary computing. In: *Proceedings of the IEEE IECON2004*. IECON2004, Busan, South Korea, pp. 1268–1272.

Manderick, B. & Spiessens, P. 1989 Fine-grained parallel genetic algorithm. In: *Proceedings of the Third International Conference on Genetic Algorithms*. Morgan Kaufmann Publishers Inc., San Francisco, CA, pp. 428–433.

Mantoglou, A. & Kourakos, G. 2007 Optimal groundwater remediation under uncertainty using multi-objective optimization. *Water Resources Management* 21 (5), 835–847.

McKinney, D. C. & Lin, M. D. 1994 Genetic algorithm solution of groundwater management models. *Water Resources Research* 30 (6), 1897–1906.

Mcraebetne, T., Kawamura, A., Jinno, K. & Olsson, J. 2002 Risk assessment for optimal drought management of an integrated water resources system using a genetic algorithm. *Hydrological Processes* 16 (11), 2189–2208.

Mohan, S. A. & Babu, K. J. 2010 Optimal water distribution network design with honey-bee mating optimization. *Journal of Computing in Civil Engineering* 24 (1), 117–126.

Montaseri, M., Afshar, M. H. & Bozorg-Haddad, O. 2015 Development of simulation-optimization model (MUSIC-GA) for urban stormwater management. *Water Resources Management* 29, 4649–4665.

Mostafaei, A., Forootan, E., Safari, A. & Schumacher, M. 2018 Comparing multi-objective optimization techniques to calibrate a conceptual hydrological model using in situ runoff and daily GRACE data. *Computational Geosciences* 22 (5), 789–814.

Muleta, M. K. & Boulos, P. F. 2007 Multiobjective optimization for optimal design of urban drainage systems. In: *World Environmental and Water Resources Congress 2007: Restoring Our Natural Habitat*, pp. 1–10.

Muleta, M. K. & Nicklow, J. W. 2005 Decision support for watershed management using evolutionary algorithms. *Journal of Water Resources Planning and Management* 131 (1), 35–44.

Munavalli, G. R. & Kumar, M. M. 2003 Optimal scheduling of multiple chlorine sources in water distribution systems. *Journal of Water Resources Planning and Management* 129 (6), 493–504.

Murthy, Z. V. P. & Vengal, J. C. 2006 Optimization of a reverse osmosis system using genetic algorithm. *Separation Science and Technology* 41 (4), 647–663.

Muschalla, D. 2008 Optimization of integrated urban wastewater systems using multi-objective evolution strategies. *Urban Water Journal* 5 (1), 59–67.
Narayanan, A. & Moore, M. 1996 Quantum-inspired genetic algorithms. In: *Proceedings of the IEEE International Conference on Evolutionary Computation*, Nagoya, Japan. pp. 61–66.

Nickabadi, A., Ebadi-Taleh, M. M. & Safabakhsh, R. 2008 DNPSO: a dynamic niching particle swarm optimizer for multi-modal optimization. In: *Evolutionary Computation*, 2008. CEC 2008. IEEE, Hong Kong. pp. 26–32.

Nicklow, J., Reed, P., Savic, D., Dessalegne, T., Harrell, L., Chan-Hilton, A. & Zeeman, E. 2010 *State of the art for genetic algorithms and beyond in water resources planning and management*. *Journal of Water Resources Planning and Management* 136 (4), 412–432.

Nixon, J. B., Dandy, G. C. & Simpson, A. R. 2001 A genetic algorithm for optimizing off-farm irrigation scheduling. *Journal of Hydroinformatics* 3 (1), 11–22.

Oliveira, R. & Loucks, D. P. 1997 Operating rules for multiservoir systems. *Water Resources Research* 33 (4), 839–852.

Ostermeier, A., Gawelczyk, A. & Hansen, N. 1994a A derandomized approach to self-adaptation of evolution strategies. *Evolutionary Computation* 2 (4), 369–380.

Ostermeier, A., Gawelczyk, A. & Hansen, N. 1994b Step-size adaption based on non-local use of selection information. In: *Parallel Problem Solving From Nature – PPSN III*, Jerusalem, Israel, pp. 189–198.

Ostfeld, A. & Salomons, E. 2006 Sensor network design proposal for the battle of the water sensor networks (BWSN). In: *8th Annual Water Distribution Systems Analysis Symposium*, Cincinnati, OH, pp. 1–16.

Ouyang, Q., Lu, W., Hou, Z., Zhang, Y., Li, S. & Luo, J. 2017 Chance-constrained multi-objective optimization of groundwater remediation design at DNAPL-contaminated sites using a multi-algorithm genetically adaptive method. *Journal of Contaminant Hydrology* 200, 15–23.

Park, D. K., Ko, N. Y. & Lee, K. K. 2007 Optimal groundwater remediation design considering effects of natural attenuation processes: pumping strategy with enhanced-natural-attenuation. *Geosciences Journal* 11 (4), 377–385.

Parouha, R. P. & Das, K. N. 2016 A memory based differential evolution algorithm for unconstrained optimization. *Applied Soft Computing* 38, 501–517.

Patil, M. B., Naidu, M. N., Vasan, A. & Varma, M. R. 2020 Water distribution system design using multi-objective particle swarm optimisation. *Sadhana* 45 (1), 21.

Penn, R., Friedler, E. & Ostfeld, A. 2013 Multi-objective evolutionary optimization for greywater reuse in municipal sewer systems. *Water Research* 47 (15), 5911–5920.

Perez-Pedini, C., Limbrunner, J. F. & Vogel, R. M. 2005 Optimal location of infiltration-based best management practices for storm water management. *Journal of Water Resources Planning and Management* 131 (6), 441–448.

Prasad, T. D. & Park, N. S. 2004 Multiobjective genetic algorithms for design of water distribution networks. *Journal of Water Resources Planning and Management* 130 (1), 73–82.

Prasad, T. D. & Tanyimboh, T. T. 2008 Entropy based design of any town water distribution network. In: *Water Distribution Systems Analysis*, 2008, pp. 1–12.

Prasad, T. D., Walters, G. A. & Savic, D. A. 2004 Booster disinfection of water supply networks: multiobjective approach. *Journal of Water Resources Planning and Management* 130 (5), 367–376.

Price, K., Storn, R. M. & Lampinen, J. A. 2005 *Differential Evolution: A Practical Approach to Global Optimization*. Springer Verlag, Berlin. ISBN 978-3-540-20950-8.

Qin, A. K. & Saganthan, P. N. 2005 Self-adaptive differential evolution algorithm for numerical optimization. In: *IEEE Congress on Evolutionary Computation*, IEEE, Edinburgh, UK, Vol. 2, pp. 1785–1791.

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 (5), 1–11. https://doi.org/10.1029/2009WR007785.

Raju, K. S. & Kumar, D. N. 2004 Irrigation planning using genetic algorithms. *Water Resources Management* 18 (2), 163–176.

Raju, K. S., Vasan, A., Gupta, P., Ganesan, K. & Mathur, H. 2012 Multi-objective differential evolution application to irrigation planning. *ISH Journal of Hydraulic Engineering* 18 (1), 54–64.

Rani, D. & Moreira, M. M. 2010 Simulation-optimization modeling: a survey and potential application in reservoir systems operation. *Water Resources Management* 24, 1107–1138.

Rao, Z. & Salomons, E. 2007 Development of a real-time, near-optimal control process for water-distribution networks. *Journal of Hydroinformatics* 9 (1), 25–37.

Raseman, W. J., Kasprzyk, J. R. & Summers, R. S. 2020 Multi-objective optimization of water treatment operations for disinfection byproduct control. *Environmental Science-Water Research and Technology* 6 (5), 702–714.

Rauch, W. & Harremoes, P. 1999 Genetic algorithms in real time control applied to minimize transient pollution from urban wastewater systems. *Water Research* 33 (5), 1265–1277.

Rechenberg, I. 1973 *Evolution strategie: Optimierung technis-cher systeme nach prinzipien der biologischen evolution*. Frommann-Holzboog Verlag, Stuttgart.

Reddy, M. J. 2006 *Swarm Intelligence and Evolutionary Computation for Single and Multiobjective Optimization in Water Resource Systems*. PhD Thesis, Indian Institute of Science, Bangalore.

Reddy, M. J. 2009 Swarm intelligence techniques and its applications in water resources management. *ISH Journal of Hydraulic Engineering* 15 (SP.1), 151–169.

Reddy, M. J. & Kumar, D. N. 2006 Optimal reservoir operation using multi-objective evolutionary algorithm. *Water Resources Management* 20 (6), 861–878.

Reddy, M. J. & Kumar, D. N. 2007a Optimal reservoir operation for irrigation of multiple crops using elitist-mutated particle swarm optimization. *Hydrological Sciences Journal, IAHS* 52 (4), 686–701.
Reddy, M. J. & Kumar, D. N. 2007b Multi-objective particle swarm optimization for generating optimal trade-offs in reservoir operation. *Hydrological Processes: An International Journal* 21 (21), 2897–2909.

Reddy, M. J. & Kumar, D. N. 2007c Multiobjective differential evolution with application to reservoir system optimization. *Journal of Computing in Civil Engineering* 21 (2), 136–146.

Reddy, M. J. & Kumar, D. N. 2008 Evolving strategies for crop planning and operation of irrigation reservoir system using multi-objective differential evolution. *Irrigation Science* 26 (2), 177–190.

Reddy, M. J. & Kumar, D. N. 2009 Performance evaluation of elitist-mutated multi-objective particle swarm optimization for integrated water resources management. *Journal of Hydroinformatics* 11 (1), 79–88.

Reddy, M. J. & Kumar, D. N. 2012 Computational algorithms inspired by biological processes and evolution. *Current Science* 103 (4), 1–11.

Reed, P. M., Hadka, D., Herman, J. D., Kasparyk, J. R. & Kollat, J. B. 2013 Evolutionary multiobjective optimization in water resources: the past, present, and future. *Advances in Water Resources* 51 (2013), 438–456.

Ritzel, B. J., Eheart, J. W. & Ranjithan, S. 1994 Using genetic algorithms to solve a multiple objective groundwater pollution containment problem. *Water Resources Research* 30 (5), 1589–1603.

Rocha, L. M. 1995 Contextual genetic algorithms: evolving developmental rules. In: *Advances in Artificial Life* (F. Moran, A. Moreno, J. J. Merelo & P. Chacon, eds). Lecture Notes in Artificial Intelligence, Springer-Verlag. pp. 368–382.

Sala, R., Baldanzini, N. & Pierini, M. 2017 SQG-differential evolution for difficult optimization problems under a tight function evaluation budget. In: *Proceedings of the International Workshop on Machine Learning, Optimization, and Big Data*. Springer, Cham, pp. 322–336.

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 (2), 67–77.

Savic, D. A., Walters, G. A. & Schwab, M. 1997 April Multiobjective genetic algorithms for pump scheduling in water supply. In: *AISB International Workshop on Evolutionary Computing*. Springer, Berlin, Heidelberg, pp. 227–235.

Seyedpour, S. M., Kirmizakis, P., Brennan, P., Doherty, R. & Ricken, T. 2019 Optimal remediation design and simulation of groundwater flow coupled to contaminant transport using genetic algorithm and radial point collocation method (RPBCM). *Science of The Total Environment* 669, 389–399.

Shamsudin, S., Dan’azumi, S. & Yusop, A. A. Z. 2014 Optimum combination of pond volume and outlet capacity of a stormwater detention pond using particle swarm optimization. *Urban Water Journal* 11 (2), 127–136.

Shi, Y. & Eberhart, R. C. 1998 A modified particle swarm optimizer. In: *Proceedings of IEEE International Conference on Evolutionary Computation*. IEEE, Anchorage, AL, pp. 69–73.

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 (12), 4075–4094.

Shieh, H. J. & Peralta, R. C. 2005 Optimal in situ bioremediation design with hybrid genetic algorithm-simulated annealing. *Journal of Water Resources Planning and Management* 131 (1), 67–78.

Shin, M. J. & Choi, Y. S. 2018 Combining an r-based evolutionary algorithm and hydrological model for effective parameter calibration. *Water* 10 (10), 1359.

Simpson, A. R., Dandy, G. C. & Murphy, L. J. 1994 Genetic algorithms compared to other techniques for pipe optimization. *Journal of Water Resources Planning and Management* 120 (4), 423–443.

Singh, T. S. & Chakrabarty, D. 2011 Multiobjective optimization of pump-and-treat-based optimal multilayer aquifer remediation design with flexible remediation time. *Journal of Hydrologic Engineering* 16 (5), 413–420.

Singh, A., Minsker, B. S. & Valocchi, A. J. 2008 An interactive multi-objective optimization framework for groundwater inverse modeling. *Advances in Water Resources* 31 (10), 1269–1283.

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 (2), 198–212.

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 (7), 04020048.

Smalley, J. B., Minsker, B. S. & Goldberg, D. E. 2000 Risk-based in situ bioremediation design using a noisy genetic algorithm. *Water Resources Research* 36 (10), 3043–3052.

Song, J., Yang, Y., Chen, G., Sun, X., Lin, J., Wu, J. & Wu, J. 2019 Surrogate assisted multi-objective robust optimization for groundwater monitoring network design. *Journal of Hydrology* 577, 125994.

Srinivas, N. & Deb, K. 1994 Multiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary Computation* 2 (3), 221–248.

Storn, R. & Price, K. 1996 Minimizing the real functions of the ICEC’96 contest by differential evolution. In: *Proceedings of the IEEE International Conference on Evolutionary Computation*. IEEE, Nagoya, Japan, pp. 842–844.

Storn, R. & Price, K. 1997 Differential evolution – a simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization* 11 (4), 341–359.

Stützle, T. & Hoos, H. H. 2000 MAX MIN ant system. *Future Generation Computer Systems* 16, 889–914.

Sun, M. & Zheng, C. 1999 Long-term groundwater management by a modflow based dynamic optimization tool 1. *JAWRA Journal of the American Water Resources Association* 35 (1), 99–111.

Suribabu, C. R. 2010 Differential evolution algorithm for optimal design of water distribution networks. *Journal of Hydroinformatics* 12 (1), 66–82.
Swan, R., Bridgeman, J. & Sterling, M. 2017 Optimisation of water treatment works performance using genetic algorithms. *Journal of Hydroinformatics* **19**(5), 719–735.

Takagi, H. 2001 Interactive evolutionary computation: fusion of the capabilities of EC optimization and human evaluation. *Proc IEEE* **89**(9), 1275–1296.

Tang, Y., Reed, P. M. & Kollat, J. B. 2007 Parallelization strategies for rapid and robust evolutionary multiobjective optimization in water resources applications. *Advances in Water Resources* **30**(5), 335–353.

Tian, F., Hu, H., Sun, Y., Li, H. & Lu, H. 2019 Searching for an optimized single-objective function matching multiple objectives with automatic calibration of hydrological models. *Chinese Geographical Science* **29**(6), 934–948.

Tigkas, D., Christelis, V. & Tsakiris, G. 2016 Comparative study of evolutionary algorithms for the automatic calibration of the Medbasin-D conceptual hydrological model. *Environmental Processes* **3**(3), 629–644.

Trivedi, A., Sanjai, K., Verma, P. & Srinivasan, D. 2017 A unified differential evolution algorithm for constrained optimization problems. In: *Proceedings of the IEEE Congress on Evolutionary Computation (CEC2017)*, IEEE, San Sebastian, Spain, pp. 1231–1238.

Tsai, M. J. & Chang, C. T. 2001 Water usage and treatment network design using genetic algorithms. *Industrial and Engineering Chemistry Research* **40**(22), 4874–4888.

Tseng, H.-E., Chang, C.-C., Lee, S.-C. & Huang, Y.-M. 2018 A block-based genetic algorithm for disassembly sequence planning. *Expert System Applications* **96**, 492–505.

Vairavamoorthy, K. & Ali, M. 2005 Pipe index vector: a method to improve genetic-algorithm-based pipe optimization. *Journal of Hydraulic Engineering* **131**(12), 1117–1125.

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**(6), 467–476.

Van Zyl, J. E., Savic, D. A. & Walters, G. A. 2004 Operational optimization of water distribution systems using a hybrid genetic algorithm. *Journal of Water Resources Planning and Management* **130**(2), 160–170.

Vasan, A. & Simonovic, S. P. 2010 Optimization of water distribution network design using differential evolution. *Journal of Water Resources Planning and Management* **136**(2), 279–287.

Vojinovic, Z., Sahlu, S., Torres, A. S., Seyoum, S. D., Anvarifar, F., Matungulu, H., Barreto, W., Savic, D. & Kapelan, Z. 2014 Multi-objective rehabilitation of urban drainage systems under uncertainties. *Journal of Hydroinformatics* **16**(5), 1044–1061.

Walters, G. A. & Lohbeck, T. 1993 Optimal layout of tree networks using genetic algorithms. *Engineering Optimization* **22**(1), 27–48.

Walters, G. A. & Smith, D. K. 1995 Evolutionary design algorithm for optimal layout of tree networks. *Engineering Optimization* **24**(4), 261–281.

Wang, Q. J. 1991 The genetic algorithm and its application to calculating conceptual rainfall-runoff models. *Water Resources Research* **27**(9), 2467–2471.

Wang, C. G. & Jamieson, D. G. 2002 An objective approach to regional wastewater treatment planning. *Water Resources Research* **38**(3), 4–1.

Wang, Y.-J. & Zhang, J.-S. 2007 Global optimization by an improved differential evolutionary algorithm. *Applied Mathematics and Computation* **188**, 669–680.

Wang, M. & Zheng, C. 1997 Optimal remediation policy selection under general conditions. *Groundwater* **35**(5), 757–764.

Wang, Y., Li, B., Weise, T., Wang, J., Yuan, B. & Tian, Q. 2011a Self-adaptive learning based particle swarm optimization. *Information Science* **181**, 4515–4538.

Wang, Y., Cai, Z. & Zhang, Q. 2011b Differential evolution with composite trial vector generation strategies and control parameters. *IEEE Transactions on Evolutionary Computation* **15**(1), 55–66.

Wang, Q., Zhou, Q., Lei, X. & Savić, D. A. 2018 Comparison of multiobjective optimization methods applied to urban drainage adaptation problems. *Journal of Water Resources Planning and Management* **144**(11), 04018070.

Wardlaw, R. & Sharif, M. 1999 Evaluation of genetic algorithms for optimal reservoir system operation. *Journal of Water Resources Planning and Management* **125**(1), 25–33.

Whitley, D., Rana, S. & Heckendorn, R. B. 1998 The island model genetic algorithm: on separability, population size and convergence. *Journal of Computing and Information Science in Engineering* **7**, 33–47.

Wierstra, D., Schaul, T., Peters, J. & Schmidhuber, J. 2008 Natural evolution strategies. In: *Proceedings of the IEEE Congress on Evolutionary Computation*, IEEE, Hong Kong, pp. 3381–3387.

Wu, Z. Y. & Walski, T. 2005 Self-adaptive penalty approach compared with other constraint-handling techniques for pipeline optimization. *Journal of Water Resources Planning and Management* **131**(3), 181–192.

Wu, J., Zheng, C., Chien, C. C. & Zheng, L. 2006 A comparative study of Monte Carlo simple genetic algorithm and noisy genetic algorithm for cost-effective sampling network design under uncertainty. *Advances in Water Resources* **29**(6), 899–911.

Yakowitz, S. 1982 Dynamic programming applications in water resources. *Water Resources Research* **18**, 673–696.

Yandamuri, S. R., Srinivasan, K. & Murty Bhallamudi, S. 2006 Multiobjective optimal waste load allocation models for rivers using nondominated sorting genetic algorithm-II. *Journal of Water Resources Planning and Management* **132**(3), 133–143.

Yang, X. S. 2007 *Firefly Algorithm*. Nature-Inspired Metaheuristic Algorithms, pp. 79–90.

Yang, X. S. 2010 A new metaheuristic bat-inspired algorithm. In: *Nature Inspired Cooperative Strategies for Optimization (NISCO 2010)* Studies in Computational Intelligence. Springer, Berlin and Heidelberg, Vol. 284, pp. 65–74.
Yang, X. S. & Deb, S. 2010 Engineering optimisation by Cuckoo search. *International Journal of Mathematical Modelling and Numerical Optimization* 1 (4), 530.

Yang, M., Cai, Z., Li, C. & Guan, J. 2014 An improved JADE algorithm for global optimization. In: *IEEE Congress on Evolutionary Computation (CEC)*, pp. 806–812.

Yazdi, J. 2018 Water quality monitoring network design for urban drainage systems, an entropy method. *Urban Water Journal* 15 (3), 227–233.

Yazdi, J., Sadollah, A., Lee, E. H., Yoo, D. G. & Kim, J. H. 2017a Application of multi-objective evolutionary algorithms for the rehabilitation of storm sewer pipe networks. *Journal of Flood Risk Management* 10 (3), 326–338.

Yazdi, J., Yoo, D. G. & Kim, J. H. 2017b Comparative study of multi-objective evolutionary algorithms for hydraulic rehabilitation of urban drainage networks. *Urban Water Journal* 14 (5), 483–492.

Yeh, W. W.-G. 1985 Reservoir management and operations models: a state-of-the-art review. *Water Resources Research* 21, 1797–1818.

Yeh, C. H. & Labadie, J. W. 1997 Multiobjective watershed-level planning of storm water detention systems. *Journal of Water Resources Planning and Management* 123 (6), 336–343.

Yoon, J. H. & Shoemaker, C. A. 2001 Improved real-coded GA for groundwater bioremediation. *Journal of Computing in Civil Engineering* 15 (3), 224–231.

Yu, W. & Zhang, J. 2011 Multi-population differential evolution with adaptive parameter control for global optimization. In: *Proceedings of the GECCO 2011*, Dublin, pp. 1093–1098.

Zahraie, B., Kerachian, R. & Malekmohammadi, B. 2008 Reservoir operation optimization using adaptive varying chromosome length genetic algorithm. *Water International* 33 (3), 380–391.

Zhan, Z. H., Zhang, J., Li, Y. & Chung, H. S. 2009 Adaptive particle swarm optimization. *IEEE Transactions on Systems, Man, and Cybernetics Part B: Cybernetics* 39 (6), 1362–1381.

Zhang, X., Srinivasan, R., Zhao, K. & Liew, M. V. 2009 Evaluation of global optimization algorithms for parameter calibration of a computationally intensive hydrologic model. *Hydrological Processes: An International Journal* 23 (3), 430–441.

Zheng, C. & Wang, P. P. 2002 A field demonstration of the simulation-optimization approach for remediation system design. *Groundwater* 40 (3), 258–266.

Zou, R. & Lung, W. S. 2004 Robust water quality model calibration using an alternating fitness genetic algorithm. *Journal of Water Resources Planning and Management* 130 (6), 471–479.

First received 7 April 2020; accepted in revised form 22 May 2020. Available online 11 June 2020