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

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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 article 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.

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Graphical Abstract
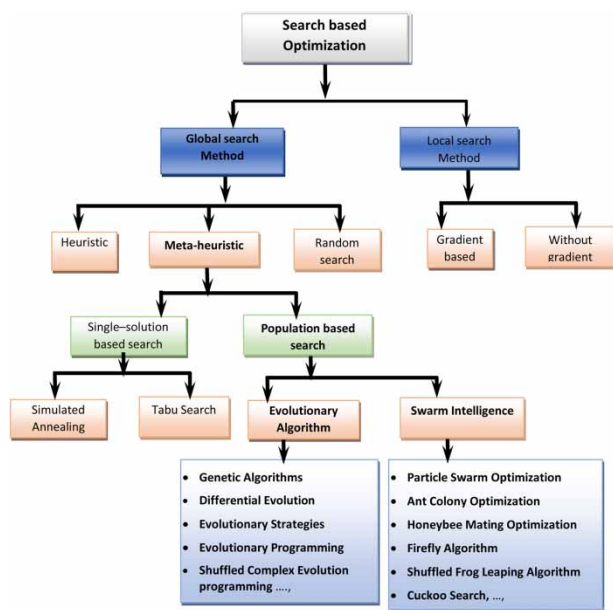
INTRODUCTION

Over the last few decades, there is a 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 optimization tools, 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.
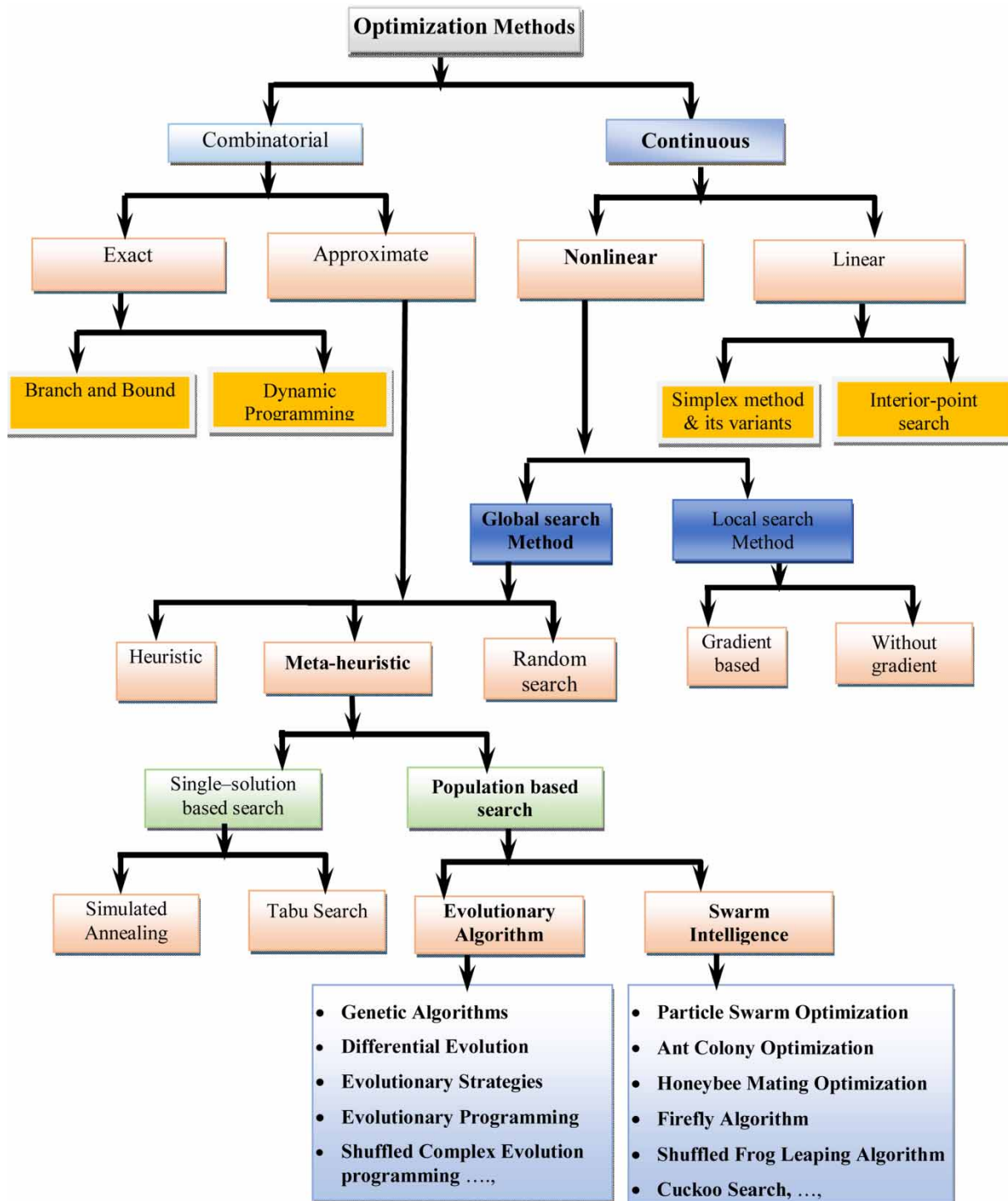
Figure 1 | Taxonomy of optimization methods.

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

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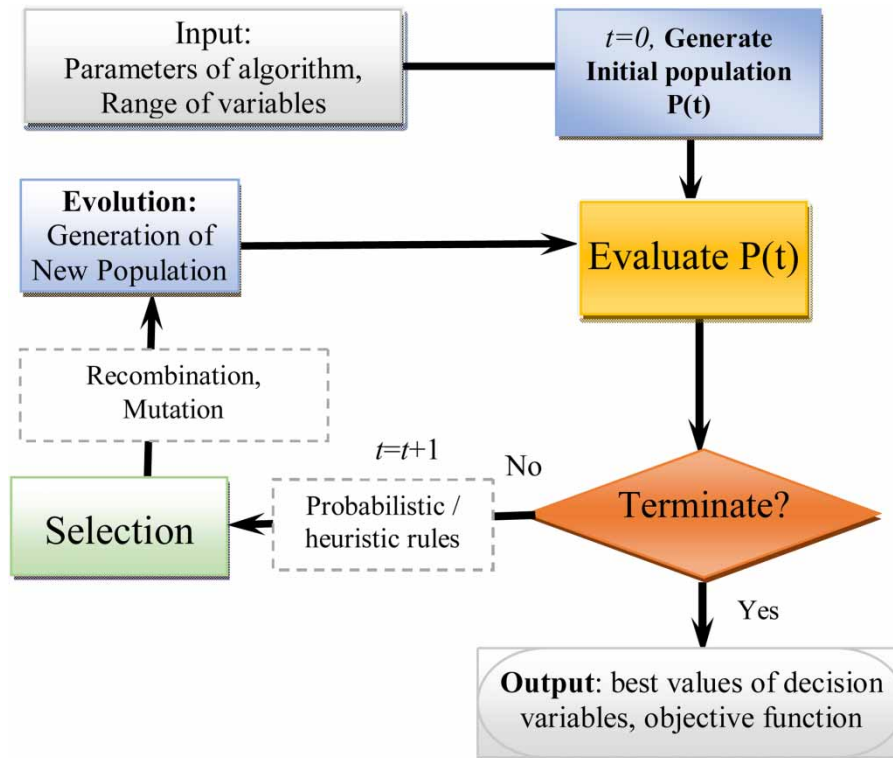
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Figure 2 | The basic structure of an evolutionary algorithm (EA).

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 offsprings
   (c) Evaluate the individual fitness of the offsprings
   (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.

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 offsprings, 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
1:  begin
2:  define problem dimension (D), generate initial population P₀ of size NP
3:  evaluate the fitness of  NP individuals in P₀
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 Pₜ₊₁ from the parents using
8:  |  crossover operation
9:  |    perform mutation on new generation Pₜ₊₁
10: |    evaluate the fitness of population Pₜ₊₁
11: |    t ← t+1
    |    end
12: end
```

```
(b)  DE algorithm
1:  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: |   end
13: |   g ← g+1
14: 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 offsprings. 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 1989), 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 (Janson *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 Differential Evolution (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
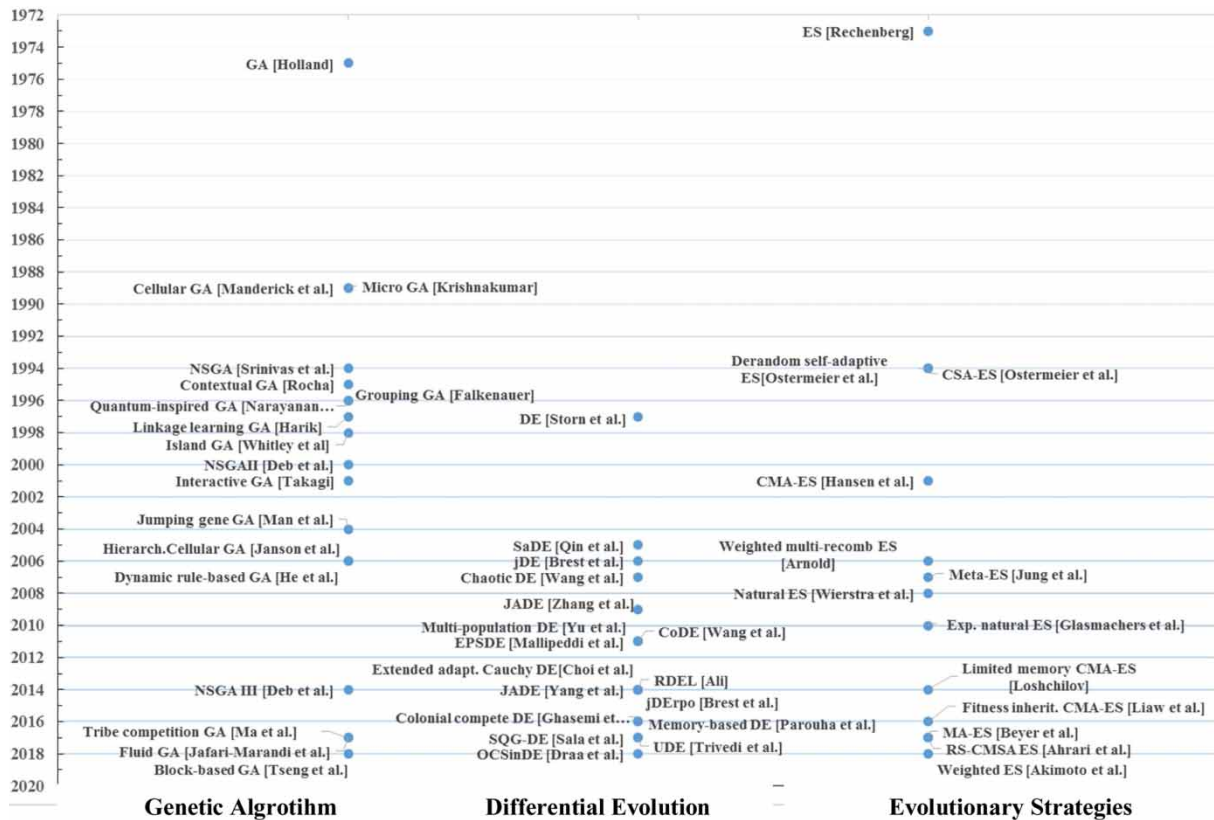
Figure 4 | Evolution of different evolutionary algorithms and their variants developed over the years, showing for genetic algorithms (GA), differential evolution (DE), and evolution strategies (ES).

exponential) used (Storn & Price 1997). For example, in *DE/rand-to-best/1/bin* variant of DE: pertur-bation 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 *et al.* 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.* 2011a, 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.

Evolutionary strategies

Evolutionary Strategies (ES) model evolution as a process of the adaptive behavior of individual ES (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 $x \in \mathfrak{K}^n$ of object variables by adding a normally distributed random variable with expectation zero and standard deviation σ 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 (μ, λ). Both of these ES work on populations rather than single individuals and are referred to as multi-membered ESs. A $(\mu + \lambda)$ ES creates λ off-springs from μ parents and selects the best μ individuals from the combined set of μ parents plus λ off-springs to make the next population. A (μ, λ) ES, on the other hand, creates λ off-springs and selects the best μ 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 1994b), CSA-ES (Ostermeier *et al.* 1994a, 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

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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 nondominance 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

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(a) **Particle swarm optimization algorithm**

```
1: begin
2: Initialize population: swarm positions X(0) and velocities V(0)
3: evaluate the fitness of the individuals
4: initialize iteration counter t ← 0
5: while termination criterion not satisfied do
6:    │ Find personal best of each particle Pbest(t)
7:    │ Find global best among all the particles Gbest(t)
8:    │ Compute velocity V(t +1)
9:    │ Compute position X(t +1)
10:   │ Restrict the positions to pre-defined range
11:   │ evaluate the fitness of the population
12:   │ t ← t+1
      End while
13: end
```

(b) **Ant colony optimization algorithm**

```
1: begin
2: Input: size of ants, parameters of algorithms
3: Structure the given problem as a graph of multi-node/multi-stage problem,
   Select heuristic information, pheromone updating rules
4: initialize iteration counter t ← 0
5: while termination criterion not satisfied do
6:    │ Position each ant in a starting node
7:    │ Repeat
8:    │    │ for each ant do
9:    │    │     Choose next node by applying the state transition rule
10:   │    │     Apply step by step pheromone update
11:   │    │ End for
12:   │ Until every ant has built a solution
13:   │ calculate the fitness and update best solution
14:   │ Apply offline pheromone update
      │ t ← t+1
15:   │ End while
16: end
```

Figure 5 | The pseudo-codes of swarm intelligence algorithms: (a) particle swarm optimization (PSO), (b) ant colony optimization (ACO).

et al. 2010), Self-adaptive learning PSO (Wang *et al.* 2011a, 2011b), 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),
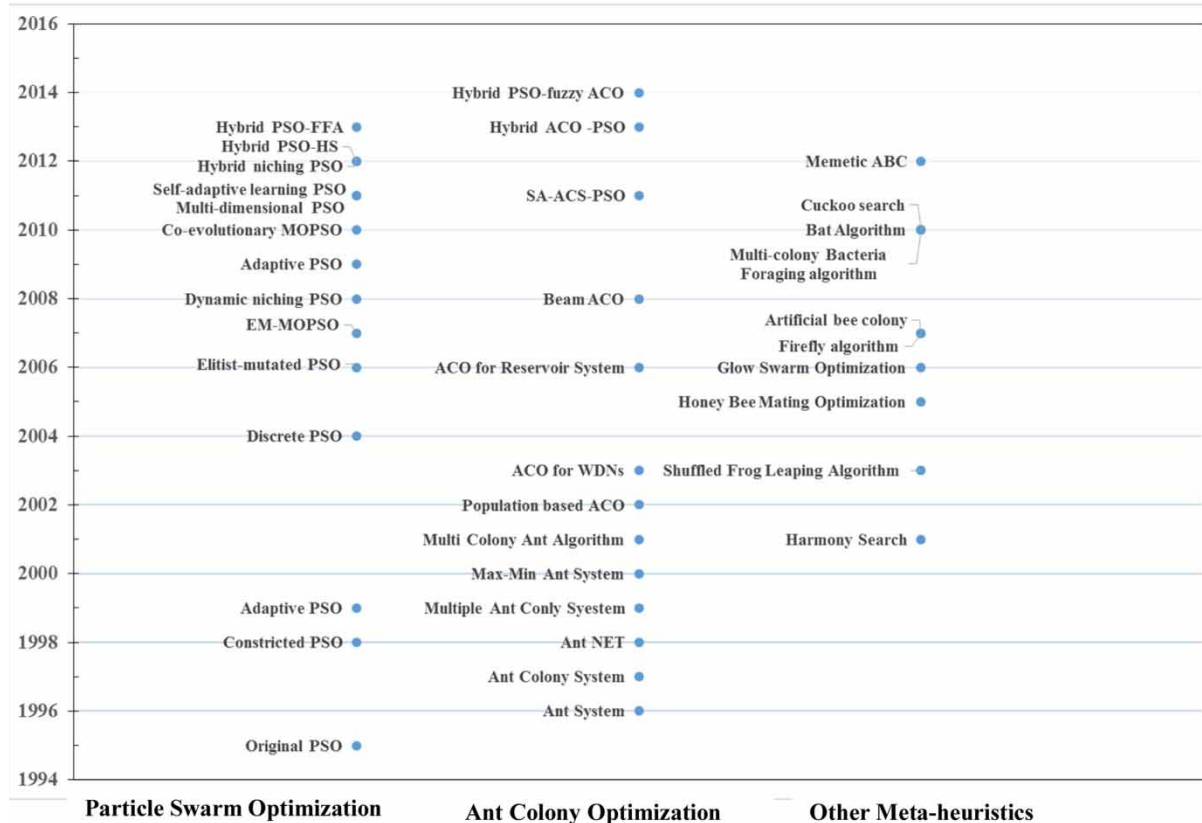
Figure 6 | Evolution of different swarm intelligence algorithms and their different variants developed over the years, showing for particle swarm optimization (PSO), ant colony optimization (ACO), and artificial bee colony (ABC) and other meta-heuristics.

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 & Stutzle 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 Gas, 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 & Dorigo1998), 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

(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 method-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 showed 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

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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; Vamvakeridou-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; 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 overflow 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.*

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Table 2 | Applications of evolutionary algorithms (EA), swarm intelligence (SI) meta-heuristic methods for single-objective optimization of water distributions systems

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.

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Table 2 | 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 efficacy of the model for minimization of cost and maximization of benefits	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
Keedwell & Khu (2005)	GA	Proposed cellular automation for network design algorithm–Genetic Algorithm (CANDA-GA) approach for initial seeding of the GA algorithm and applied for WDN design with the objective of minimization of cost	Two-loop, two industry networks	CANDA-GA gave faster convergence of the algorithm and better solutions with the same computational efforts than traditional GA
Rao & Salomons (2007)	GA	The combined use of ANN for predicting the consequences of different pump and valve control settings and GA for selecting the best combination of those settings to minimize the energy cost of meeting the current and future demands	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
Munavalli & Kumar (2003)	GA	Application of niched operator and creep mutation GA for optimal scheduling of 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	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
Eusuff & Lansey (2003)	Shuffled Frog Leaping Algorithm (SFLA)	Application of SFLA for WDN design problem for minimization of cost of pipes	Two-loop, Hanoi, and New York Tunnel (NYT) WDNs	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
Geem (2006)	Harmony search (HS) algorithm	Application of HS for WDN design and comparison of results with other meta-heuristic algorithms with the objective of minimization of cost of pipes	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

(*Continued.*)

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 Tukum-zone, 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 Khorramshahr city in Iran	GSA converged faster for Hanoi and Khorramshahr 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.

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Table 3 | Applications of multi-objective evolutionary algorithms for the multi-objective design of water distributions 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. The incorporation of network resilience in multi-objective optimization leads to a considerable reduction in computational time
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 non-linearity. The drawback is that it needs two additional parameters, minimum chromosome age and several samples, which require some tuning

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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 (2008)	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 Three optimization methods are employed: NSGA-II, a heuristic method and a combination of heuristic and NSGA-II for minimization of life cycle cost and maximization of modified resilience index (MRI)	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

(Continued.)

Table 3 | Continued

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 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

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2006; Muleta & Boulos 2007; Barreto *et al.* 2010; Penn *et al.* 2013; Vojinovic *et al.* 2014; Yazdi *et al.* 2017a; Wang *et al.* 2018), Nondomination Sorting Differential Evolution (NSDE; Yazdi 2017b), etc. The specific details of these applications are also given in Table 4.

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.* 2013; Aminjavaheri *et al.* 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 *et al.* 2018), etc. More details of the applications and their findings are given in Table 7.

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Table 4 | Applications of EA and SI meta-heuristic methods for optimization of urban drainage and sewer systems

Author(s) (year)	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 (Cellular Automata and GA)	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

(*Continued.*)

Table 4 | Continued

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

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Table 4 | Continued

Author(s) (year)	Technique used	Work and objectives	Case studies/problems considered	Key findings
Yazdi *et al.* (2017b)	SPEA-II, NSGA-II, and two extended versions of HS and DE, NSHS and NSDE	A comparative application of different MOEAs for hydraulic rehabilitation of urban drainage networks for minimization of cost of rehabilitation and minimization of the flooding overflow volume	Gasan, Sungsan, Yongdub, and Singil network	The NSHS outperformed other algorithms by generating the best Pareto-optimal solutions for the problem
Yazdi (2018)	DE	Application of DE to find the best monitoring sites based on maximizing the joint entropy obtained by information associated with water quality time series	Drainage network in Tehran, Iran	The entropy-based method leads to a high level of information content with a significantly smaller number of monitoring sites as compared to the other designs
Wang *et al.* (2018)	NSGA-II, MLOT, and GALAXY	A comparison of three MOEAs for multi-objective urban drainage adaptation problems for minimization of cost and system overloading	A portion of the drainage network in the city of Hohhot	GALAXY was found to be the most efficient among the three MOEAs as it can save substantial time and effort to cope with the parameterization issue of MOEAs
Yazdi (2018)	Non-domination sorting DE (NSDE)	Resiliency-based multi-objective design of urban drainage systems using NSDE considering objectives of minimization of total flooding and rehabilitation cost and minimization of the total flooding volume	The western part of Tehran Stormwater Drainage System (TSDS)	Results showed that the optimal design obtained by the NSDE could decrease network flooding from $3.5 \times 10^6 \text{ m}^3$ to near zero with at most 23% lower investment costs relative to the traditional design

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 (1997)	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 (1999)	GA	Different alternative formulations of GA evaluated for the four reservoir problem for maximization of the benefits	Four reservoir problem formulated by Larson (1968)	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. (2001)	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. (2002)	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 (2004)	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

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Table 5 | 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

(*Continued.*)

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

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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-Flumendosae-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; 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 6 | Applications of EA and SI meta-heuristic methods for single and multi-objective optimization of water supply and/or wastewater systems

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

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Table 6 | 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.

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Table 6 | Continued

Author(s) (year)	Technique used	Work and objectives	Case studies/problems considered	Key findings
Montaseri et al. (2015)	GA	The study presented a simulation–optimization model for managing the urban stormwater using the MUSIC model as a simulator and genetic algorithm (GA) as an optimizer. The optimization model involves minimizing the total cost of the life cycle of the urban stormwater treatment devices as the objective function	The case study area located in Central Canberra, Australia	The approach helps in the identification of the most appropriate treatment train setting for the post-development scenario, considering cost and water quality aspects, and concluded that the optimized treatment devices were effective means to remove pollutants from urban stormwater runoff.
Swan et al. (2017)	NSGA-II	NSGA-II and Monte–Carlo approaches were used to optimize operational regimes in water treatment works (WTW) considering the objectives of minimizing the operating cost and failure likelihood of a WTW	The hypothetical case study data were used, which was based in a rural location with water abstracted from a lowland reach of a river that impounded in a reservoir prior to treatment.	Static models were found to be more suitable for whole WTW optimization modeling and offered the benefit of the reduced computational burden
Raseman et al. (2020)	Borg MOEA	The Borg MOEA is used to optimize water treatment problems with five objectives. The first two objectives represent the risk of violating disinfection byproduct regulations (minimize the frequency of elevated total trihalomethane and minimize the frequency of elevated Haloacetic acids), while the remaining objectives represent operating costs (minimize solids produced, minimize lime dose required, minimize carbon dioxide dose required)	The case study located in the Cache la Poudre (CLP) River in northern Colorado, and considers a hypothetical utility that must treat water from the river	The study infers that improving the resilience and affordability of existing water treatment plants is critical for the safety and financial viability of drinking water systems and simulation–optimization framework with Borg MOEA helps to generate various treatment strategies for decision making by water manager

DISCUSSION

Meta-heuristics for decision making?

The wide range of 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

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Table 7 | Applications of EA and SI meta-heuristic methods for the watershed management and fluvial systems

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, N.C.	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.

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Table 7 | 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 damages 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

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Table 7 | Continued

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

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

Table 8 | Applications of EA and SI meta-heuristic methods for calibration or parameter estimation of hydrological models

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 (YRHW), 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.

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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 (R^2) 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

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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)	ε-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.

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.

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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 non-linear 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 (Minsker and Shoemaker, 1998) and a realistic case study from Borden site (Graham and McLaughlin, 1991; Mackay et al., 1986)	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 developed by Minsker (1995)	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.

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Table 9 | Continued

Author(s) (year)	Technique used	Work and objectives	Case studies/problems considered	Key findings
Babbar & Minsker (2006)	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.

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Table 9 | Continued

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 setup	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

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Table 9 | Continued

Author(s) (year)	Technique used	Work and objectives	Case studies/problems considered	Key findings
Alizadeh *et al.* (2018)	DE	Development and application of an entropy-based method for GW monitoring network design for maximization of the actual (net) value of the information among wells	Eshtehard aquifer monitoring network in the central part of Iran	The DE optimization-entropy yields better performance with a larger amount of information content than the clustering and the estimation error methods
Seyedpour *et al.* (2019)	GA	Development of a coupled groundwater flow and reactive transport of contaminant and oxidant using the Multi-quadratic Radial Basis Function (MRBF) in the Meshfree method, and optimization of the GW remediation problem considering maximization of remediation contaminant concentration and minimization of the cost of the remediation process	A point source of 0.5% w/v potassium permanganate solution was constructed in a sandbox to map the change groundwater plume distribution over time.	The optimization methodology employed leads to not only delay in the reaching time of the contaminant to the d/s region but also decrease in the contaminant concentration.
Song *et al.* (2019)	ε-multi-objective noisy memetic algorithm (ε-MONMA)	Optimal design of groundwater monitoring network using a surrogate for modeling the uncertainty in k-field considering minimization of the monitoring cost, and error objective functions in terms of the mass of contaminant plume, the estimated center of contaminant plume, and contaminant concentrations	A hypothetical unconfined aquifer 600 m in longitudinal extent, 400 m in transverse extent, and a model thickness of 10 m	The ε-MONMA gave a good performance. The surrogate assisted design outperforms the deterministic and Monte Carlo simulation-based design in terms of huge savings in the computational time.

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 design 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.

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Table 10 | Comparison of basic characteristics and quality performance features of different evolutionary algorithms of genetic algorithms (GA), differential evolution (DE), and evolution strategies (ES); and swarm intelligence algorithms of particle swarm optimization (PSO), ant colony optimization (ACO), and artificial bee colony (ABC) algorithms

Feature/algorithm	GA	DE	ES	PSO	ACO	ABC
Representation	Binary or real valued	Real-valued	Real-valued	Real valued	Discrete, graphical representation	Real valued
Fitness	Scaled objective value	Objective function value	Objective function value	Objective function value	Scaled objective value	Scaled objective value
Operations for the evolution of new solutions	Crossover (main operator), Mutation (secondary operator)	Mutation (main operator), Crossover (secondary operator)	Mutation operator (only operator)	Particle velocity and position updating rules	Updating of pheromone intensities, heuristic information	Bee position updating rules and stochastic process
Selection process	Deterministic, extinctive	Probabilistic, preservative	Probabilistic, preservative	Deterministic, extinctive	Probabilistic, preservative	Probabilistic, preservative
Suitable for nonlinear problem? type of variables	Yes, Real/discrete value	Yes, Real/discrete value	Yes, Real/discrete value	Yes, Real/discrete value	Yes, Discrete value	Yes, Discrete/real value
Preferred population size, generations (or iterations)	Small to medium, large	Small-to-medium, large	Medium, large	Larger, medium	Medium, large	Medium, large
Influence of population size on solution time	High	Low	Low	Low	Medium-to-high	Medium-to-high
Influence of best solution on population	Medium	Less	Less	High	Medium	Medium
Ability-to-parallelization of the search	Yes	Yes	Yes	Yes	Yes	Yes
Tendency for premature convergence	Medium	Low	Low-to-medium	Medium-to-high	Medium	Medium-to-high

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 one or not applicable for all types of problems, as each problem may have varying complexity depending on one dimension 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 water resources engineering area. Some of these issues and future research directions are listed below.

Improvement in algorithm and solution methodology

There is a lot 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 (how to overcome the effect of the sensitivity of

the parameters on the performance of the algorithm), recently, several studies put efforts to explore 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 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. How reliable are these solutions? (considering the changing conditions, 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 apace 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.

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